Mobile Real-Time Classification of Activities of Daily-Living in Post-Stroke Patients

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Abstract

A stroke or a cerebrovascular accident consists of a blockage or rupture of the blood flow to the brain and it is nowadays the third largest cause of death in Europe, Japan and the USA. Per year, more than 750 000 people have a stroke and, from those, 200 000 do not survive. In most cases, stroke survivors are forced to live the rest of their lives with serious impairments in one or more parts of the body. In order to decrease the impact of these physical impairments, stroke rehabilitation must be conducted as soon as possible. In this kind of rehabilitation there is a special focus on stroke patients relearning physical and cognitive skills that were lost due to the stroke. The choice of a stroke rehabilitation treatment and of methodologies for assessing patients' impairments is made according to the physiotherapist's practical experience. Therefore, we may conclude it would be useful to have an extra source of information, preferably quantitative data, about patient's daily activity, gathered outside the health facility.
Additionally, with the recent increase in popularity of mobile devices, such as smartphones, these devices have become increasingly inexpensive, portable and more ubiquitous. This has made it very interesting to use the smartphone's built-in sensors, namely the accelerometer, gyroscope and magnetometer, as a source of quantitative data for the analysis of human movement.
In this project, an activity recognition algorithm was developed, which was capable of detecting two activities of daily living: sitting/standing and eating. This algorithm used a smartphone, placed on the front pocket, and its accelerometer to measure the sitting/standing movements, by means of a threshold-based approach. This algorithm measured the total time standing, total time sitting and the number of transitions with an overall mean relative error of 6,84%. The eating movement detection was treated as a machine learning problem and used a smartwatch on the wrist. A segmentation method was applied based on the gyroscope signal and several features were extracted for the three inertial sensors and for sensor fusion combination of those. A Sequential Forward Selection step was applied to eliminate redundant features and four classification algorithms were tested: Decision Tree, k-NN, Naive Bays and SVM. Ultimately, the Decision Tree algorithm was considered the most favorable, with an accuracy of 92,99%. The whole algorithm was validated for a dataset of 26 individuals.
This algorithm was then applied in the design of an exergame for application in virtual reality stroke rehabilitation. This exergame was able to match the final score, based on patient's in-game performance, with the ICF scale.

Keywords: Stroke. Stroke Rehabilitation. Machine Learning. Smartphone. Smartwatch. Inertial Sensors. Exergame

Resumo

Um acidente vascular cerebral, vulgarmente conhecido por AVC, consiste numa ruptura ou bloqueio do fluxo sanguíneo para o cérebro a terceira principal causa de morte na Europa, Japão e EUA. Por ano, mais de 750 000 pessoas sofrem um AVC, das quais 200 000 não sobrevivem. Na maioria dos casos, um sobrevivente de um AVC é obrigado a viver o resto da sua vida com sérias debilitações em uma ou mais partes do corpo. De forma a diminuir o impacto destas debilitações físicas, deve ser realizada reabilitação pós-AVC o mais cedo possível. Neste tipo de reabilitação os pacientes reaprendem capacidades físicas e cognitivas básicas que perderam devido ao AVC.
A escolha de um tratamento de reabilitação pós-AVC e das metodologias para avaliação das debilitações do paciente é feita de acordo com a experiência do fisioterapeuta. Assim, pode-se concluir que seria extremamente útil ter um fonte adicional de informação, preferencialmente quantitativa e objectiva, sobre a actividade diária do paciente fora do establecimento de saúde.
Por outro lado, com o recente aumento de popularidade dos dispositivos móveis, como os *smartphones*, estes dispositivos têm-se tornado cada vez mais económicos, portáteis e ubíquos. Isto faz com que seja muito interessante utilizar os sensores que estão incorporados nos *smartphones*, nomeadamente o acelerómetro, giroscópio e megnetómetro, como uma fonte de informação quantitativa para a análise do movimento humano.
Neste projecto foi desenvolvido um algoritmo de reconhecimento da actividade humana que é capaz detectar duas actividades do dia-a-dia: sentar/levantar e comer. Este algoritmo utiliza um *smartphone*, colocado no bolso da frente, e o seu acelerómetro para medir o movimento de sentar/levantar, recorrendo a uma abordagem baseada em *thresholds*. Este algoritmo mede o tempo total em pé, o tempo total sentado e o número de transições, com um erro relativo médio geral de 6,84%. A detecção do movimento de comer foi tratada como um problema de *machine learning* e utiliza um *smartwatch* no pulso. Foi aplicado um método de segmentação baseado no giroscópio e foram extraídas várias características para o sinal dos três sensores e para combinações dos mesmos através de *sensor fusion*. Foram eliminadas características redundantes através de *Sequential Forward Selection* e foram testados quatro classificadores: *Decision Tree*, k-NN, Naive Bayes e SVM. Concluiu-se que a *Decision Tree* era o algoritmo mais favorável, com uma *accuracy* de 92,99%. O algoritmo completo foi validado para um *dataset* de 26 indivíduos.
Este algoritmo foi então aplicado no desenvolvimento de um *exergame* para aplicação em reabilitação pós-AVC através de realidade virtual. Este *exergame* é capaz de fazer corresponder a pontuação final, baseada na prestação do paciente no jogo, com a escala ICF.

Palavras-Chave: AVC. Reabilitação Pós-AVC. *Machine Learning*. *Smartphone*. *Smartwatch*. Sensores Inerciais. *Exergame*

"Cabecinha pensadora !"

António Rodrigues Pimenta

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List of Abbreviations

ADL	Activity of Daily Living
AHA	American Heart Association
ARFF	Attribute-Relation File Format
ASA	American Stroke Association
AUC	Area Under Curve
CIMT	Constraint-Induced Movement Therapy
CNS	Central Nervous System
CRPG	*Centro de Reabilitação Profissional de Gaia*
DRF	Device Reference Frame
ERF	Earth Reference Frame
FES	Functional Electrical Stimulation
FEUP	*Faculdade de Engenharia da Universidade do Porto*
FFT	Fast Fourier Transform
FhP-AICOS	Fraunhofer Portugal Research Center for Assistive Information and Communication Solutions
ICF	International Classification of Functioning, Disabilities and Health
IDE	Integrated Development Environment
k-NN	k-Nearest Neighbors
NDT	Neurodevelopment Treatment
ROC	Receiver Operating Characteristic
SVM	Support Vector Machine
TIA	Transient Ischemic Attack
tPA	Tissue Plasminogen Activator
WHO	World Health Organization

Chapter 1

Introduction

1.1 Motivation

Stroke is one of the leading causes of death in the developed world, namely Europe, Japan and the USA. It is divided in two categories: ischemic and hemorrhagic. Ischemic stroke happens as a result of a blockage in a blood vessel, resulting in an interruption of the blood flow to the brain. Hemorrhagic stroke results from a rupture of a blood vessel, which causes a hemorrhage and accumulation of blood in the brain. Both result in a lack of oxygen in the brain, which has several consequences, depending mainly on medical response time.

The prognosis and consequences of a stroke vary widely according to the extensiveness of the stroke. The stroke victim is affected not only in terms of physical condition, but also cognitively and emotionally. A stroke usually results in apraxia, in which the patient is unable to perform movements and gestures necessary to achieve a certain goal. This leads to a difficulty in performing daily activities and maintaining body balance. Hemiplegia is also a common prognosis of stroke, where the patient is unable to move a certain sagittal part of the body, and it may accompany spasticity, in which the muscles are on a constant state of contraction. These conditions are normally all related to the upper limb and its movement. In addition, cognitive and emotional problems such as depression, failure to express emotion and memory deficit are also factors which worsen the prognosis.

Stroke is the second leading cause of disability, which affects 75% of stroke survivors enough to decrease their employability. This leads to a great need for stroke rehabilitation in order to restore functionality to the stroke patients. This type of rehabilitation involves an extensive degree of motor re-learning, especially in the upper limb, and requires a multidisciplinary team of physical, occupational and speech/language therapists working alongside. There are several techniques being applied nowadays, but there is still a great necessity of research and alternative devices on this area. Virtual reality is an example of an emerging field that has been showing promising results in stroke rehabilitation. Moreover, the fact that stroke patients are only able to have rehabilitation through direct observation of professionals and with the intervention of certain devices makes it impossible to have it at home. Additionally, since direct observation may be subjective, there is a

need for stroke therapists to have quantitative data on their patient's status to conduct better rehabilitation.
One very common way of obtaining quantitative data on upper limb movement is by using inertial sensors. These sensors can be found in mobile devices, such as smartphones, which may be used at home. Upper limb movement may be analyzed through accelerometer, gyroscope and magnetometer data. These sensors are usually placed on upper limb joints in order to evaluate the motion of that person. Using algorithmic classifiers, the device is able to recognize certain activities through the sensor signal, and determine what type of movement the stroke patient is performing at that time. These movements include sitting/standing, walking, running, cycling, among other daily activities.
One possible application of this technology in precisely virtual reality therapy, mentioned previously. Exergames, which are games designed to promote physical activity of the person playing, urge the stroke patient to perform certain movements in order to complete levels. These games usually resort to movement recognition algorithms. Their purpose in not only promoting physical rehabilitation, but also act on a cognitive level, since they normally involve the person having to associate situations in the game with situations in real life scenarios and act accordingly. Regarding the fact that stroke rehabilitation may become tedious at some point, virtual reality therapy also presents itself as a motivational and engaging technique, which impacts the stroke patient on an emotional level, and may lead to better results.

1.2 Objectives

The goal of this dissertation is to develop an algorithm, using an Android smartphone and an Android smartwatch, both with inertial sensors, to detect and classify activities of daily living of post-stroke patients. The activities that should be detected and recognized are the sitting and standing movement and the eating movement. The smartphone is used in the pocket and the smartwatch in the wrist.
Another objective of this dissertation is to develop an exergame to serve as proof of concept for the developed algorithm. This exergame should be able to detect the aforementioned activities as in-game tasks, that should be repeated several times, contributing to the patients physical rehabilitation.

1.3 Document Structure

This dissertation is organized in chapters, each one covering a specific topic, and these are subdivided in sections that focus on specific subjects of the said topic.
The full organization is as follows:

- **Chapter 1 - Introduction**
  In this chapter, the main purpose is making a first approach to the context and objectives that will be fulfilled in this dissertation and also describing its structure.

- **Chapter 2 - Literature Review**
  In this chapter, an extended review of the literature is made. This review covers the topic of stroke, namely its definition and social impact; stroke rehabilitation, focusing on international guidelines and current techniques; mobile devices and sensors, specifically the smartphone and smartwatch and their inertial sensors; machine learning technology, mentioning aspects like feature extraction, classification and evaluation procedures.

- **Chapter 3 - Algorithm Development**
  In this chapter, the developed algorithm is described in full detail, as well as its results and a discussion of those. The algorithm is explained for both activities that are recognized in this project: sitting/standing and eating.

- **Chapter 4 - Exergame**
  In this chapter, the developed exergame is extensively explained, regarding interface, game logic and results. The exergame is contextualized in terms of stroke rehabilitation impact, specifically on the ICF scale.

- **Chapter 5 - Conclusions**
  This final chapter aims at describing what was achieved in this dissertation and referencing future developments that could be implemented.

Chapter 2

Literature Review

2.1 Stroke

2.1.1 Definition

The term “stroke” is said to have likely been first introduced as early as 1689 by William Cole and since then it has suffered several changes in meaning, due to an increasing development of technology and information. For the past 50 years, there have been serious advancements in what is known about the brain, its anatomy, functions and blood supply, resulting in an evolution of the term [7].

The current World Health Organization (WHO) definition of stroke (introduced in 1970 and still used) is “rapidly developing clinical signs of focal or global disturbance of cerebral function, lasting more than 24 hours or leading to death, with no apparent cause other than that of vascular origin.” and since then, there has been an effort from specialists towards better describing this injury. The 24-hour limit differentiates a stroke from a transient ischemic attack (TIA), which shares symptoms, but that are resolved within 24 hours; TIAs are colloquially called “warning strokes” or “mini-strokes” [7].

The American Heart Association (AHA)/American Stroke Association (ASA) have both contributed to clarify the definition, which has been leading to an expert consensus on the matter. Generally, a stroke may be characterized as a neurological focal or global injury on the central nervous system (CNS) derived from a vascular cause. The blood flow suffers some kind of disturbance and there is a consequent lack of oxygen to the CNS in order to meet the metabolic demand, which leads to a loss of brain function [8].

This disturbance may arise from different causes, which may be of ischemic or hemorrhagic nature, and it may occur in any part of the CNS, such as the brain, spinal cord or retina. Most terms are relative to the brain, since it is the most common part of the CNS where strokes occur.

A stroke is considered a medical emergency and can therefore result in serious and permanent impairments or eventually death. Consequently, a stroke patient must be immediately assisted in stroke-specialized hospital units [8].

2.1.2 Categories

2.1.2.1 Ischemic stroke

An ischemic stroke is characterized by the decrease of the blood flow to the brain, due to a blockage in the blood flow or leakage outside the vessel walls. If this happens in a confined region of the brain, it is called focal ischemia; if it encompasses wider areas of brain tissue, it is considered global ischemia. It may also be called cerebral infarction or brain ischemia [1]. On the left side of Figure 2.1 there is a representation of an ischemic stroke in the brain.

2.1.2.2 Hemorrhagic stroke

A hemorrhagic stroke consists of an accumulation of blood caused by hemorrhage as a consequence of a rupture of a weakened blood vessel. These frail blood vessels may be aneurysms or arteriovenous malformations (AVM). It is considered a focal brain injury [1]. On the right side of Figure 2.1 there is a representation of an hemorrhagic stroke in the brain.

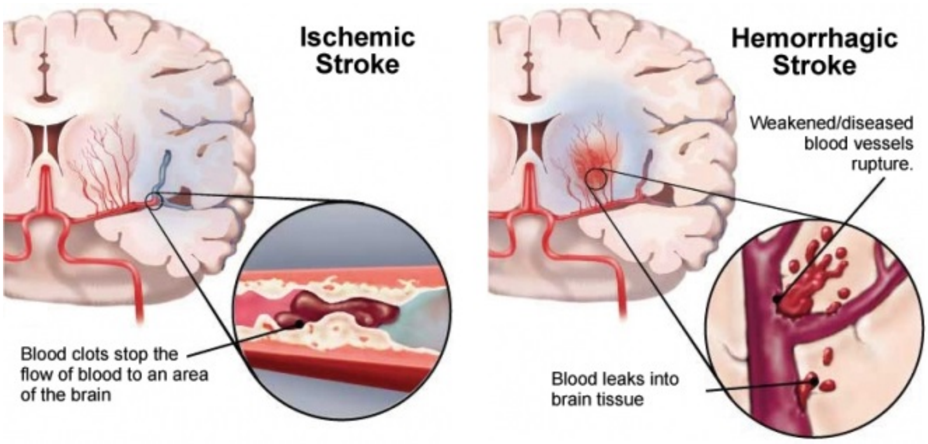

Figure 2.1: Representation of ischemic stroke (left) and hemorrhagic stroke (right) - the gray area represents oxygen deprivation [1]

2.1.3 Causes

2.1.3.1 Ischemic stroke

Thrombosis

This type of ischemic stroke happens when a thrombus or blood clot is formed around atherosclerotic plaques in the blood vessels. This thrombus reduces the vessel diameter, which leads to a blockage of the blood flow, triggering the ischemic cascade. A thrombus may lead to an embolic stroke, if a portion of the blood clot detaches from itself; at that point, that portion is called an embolus. There are two types of thrombotic ischemic stroke: large vessel disease and small vessel disease [9].

Embolism

An embolic stroke refers to the blockage of a blood vessel by an arterial embolus, which is a travelling particle in the arterial bloodstream from another source in the body. An embolus is usually a blood clot, but it may also be another particle such as fat, air, cancer cells or a composition of several particles [9].

The particularity about an embolic stroke is that since the embolus arises from elsewhere, measures to remove it are only temporary until the source is identified.

Since an embolism is a sudden event, the symptoms are usually maximal at start, but they may dissipate if the embolus travels elsewhere [9].

Cerebral Hypoperfusion

This phenomenon refers to a reduction of the blood flow to all parts of the body and it is most commonly a result of heart failure, reduction of cardiac output or bleeding. Since this reduction in blood flow is global, every part of the brain may be affected, leading to global ischemia [9].

Venous Thrombosis

As a result of locally increased venous pressure, cerebral venous thrombosis may arise, since the pressure in the veins becomes higher than the one generated by the arteries. This type of ischemic stroke is the one with the highest probability of undergoing a hemorrhagic transformation [9].

2.1.3.2 Hemorrhagic stroke

Hemorrhagic strokes often occur due to bursting of small arteries or arterioles. Common causes are hypertension, vascular malformations or amyloid angiopathy. Other potential causes are trauma, bleeding disorders or drug use [9].

2.1.4 Signs and Symptoms

A great identifying particularity of stroke signs and symptoms is their quickness to arise, over seconds to minutes, which usually do not progress further. The seriousness of a specific stroke is proportional to the extensiveness of the affected area.

Over the years there has been an effort towards determining the presence or absence of stroke to different degrees. Some general signs revolve around sudden-onset face weakness, arm drift and abnormal speech. These three key aspects originated the term FAST (Face, Arm, Speech, Time) since when at least one of these aspects was present, it increased the likelihood of correctly identifying a stroke. However, when all three were absent, the likelihood decreased accordingly [10]. Although these findings are not fully trustworthy for identifying a stroke, the fact that they can be evaluated relatively easily by any person make them a very valuable tool for assisting possible stroke victims quickly and avoiding further complications, hence the fourth term - Time. The use of the method FAST is advocated by several groups and organizations specialized in stroke and it is recommended by professional guidelines [11].

Another method for quickly addressing an eventual stroke is called ROSIER, Recognition of Stroke in the Emergency Room, which is based on features from medical history and physical examination and is also supported by stroke guidelines [10].
In most cases, symptoms are unilateral, which means they only affect one side of the body, usually corresponding to the opposite side of where the stroke has happened in the brain.
The CNS has three prominent pathways: the spinothalamic tract, corticospinal tract and dorsal column. If the area affected by the stroke contains one of these three pathways, symptoms include: hemiplegia and face muscle weakness, numbness and reduction in sensory or vibratory sensation [11].
In addition to these CNS pathways, if a stroke affects the brain stem, which gives access to most of the twelve cranial nerves, it may produce symptoms related to the function of those nerves. Symptoms include altered smell, taste, hearing or vision, dropping of the eyelid, weakness of ocular muscles, decreased gag, swallow and pupil reflexes, decreased sensation, face muscle weakness, balance disturbances, altered breathing and heart rate, inability to turn head and weakness in the tongue [11].
If there is an involvement of the cerebral cortex, symptoms may be: aphasia, dysarthria, apraxia, visual field defects, memory deficit, hemineglect, disorganized thinking, confusion and lack of insight on disability [11].
Lastly, if the cerebellum is affected, one may experience: altered walking gait, altered movement coordination, vertigo and/or disequilibrium [11].
On the other hand, if an individual suffers an increase in intracranial pressure, usually associated with hemorrhagic stroke, he may experience loss of consciousness, headache and vomiting [10].

2.1.5 Prognosis

The occurrence of a stroke affects an individual at a physical, cognitive and emotional level, or even at a combination of the three, and the consequences of a stroke vary widely depending on the location and extensiveness of the injury [12].
Regarding physical disabilities, they encompass general muscle weakness, numbness, pressure sores, pneumonia, incontinence, apraxia, general difficulties carrying out activities of daily living (ADL), falls, fatigue, appetite loss, vision loss, speech loss and pain. If the severity and/or location of the stroke are critical, it may result in coma or ultimately death. Some individuals develop seizures after a stroke, which are proportional to the severity of the stroke [12].
From an emotional standpoint, problems may arise from strokes inflicting direct and serious damage to cerebral behavioral centers or frustration as a result of difficulties in adapting to new constraints. Post-stroke emotional problems include anxiety, panic attacks, failure to express emotions, mania, depression, emotional bipolarity, apathy and psychosis. In some cases, individuals present difficulties showing emotions through facial expressions, body language and voice [12].
Lastly, in regard to cognitive defects, those include aphasia, dementia, problems with attention, memory deficit. Additionally, a post-stroke patient may actually be unaware of his own disabil-

ities, a condition which is called anosognosia, or he may be unable to attend to any task which requires him to use the side of space opposite to the damaged hemisphere [12].

2.1.6 Therapy

2.1.6.1 Ischemic stroke

Tissue Plasminogen Activator (tPA)
The protein tPA is an enzyme that catalysis the conversion of plasminogen to plasmin, the major enzyme responsible for breaking down blood clots. It does not improve chances of survival but it does increase chances of the patient suffering no disability afterwards. This treatment is viable only within a time frame of 3 hours (or 4,5 hours in specific cases), which only underlines more the importance of early stroke detection. This treatment is considered a type of thrombolysis since it is based on the destruction of the blood clot and not its removal [13].

Endovascular Procedures
These types of procedures rely on mechanically removing the blood clot, which makes them thrombectomies. In these methods, a specialist sends a catheter to the site of the blocked blood vessel in the brain. In certain occasions, these procedures are accompanied by the application of tPA to help dissolve the blood clot [13].

2.1.6.2 Hemorrhagic stroke

Endovascular Procedures
Similarly to the treatment of ischemic strokes, a catheter may also be applied when treating hemorrhagic strokes. In cases such as aneurysms or vascular malformations, a specialist may send a catheter to the stroke site, usually through a major artery in the arm or leg, which then deposits a mechanical agent to prevent rupture – coil embolization [13].

Surgical Intervention
In certain cases of hemorrhagic stroke, the patient may undergo surgery to execute aneurysm clipping. The surgeon places a small clamp at the base of the aneurysm to prevent further leakage of blood, which stops the hemorrhage [13].

2.1.7 Demographic Impact

Every year, 15 million people worldwide suffer a stroke, from which nearly six million die and another five million are left permanently disabled. Globally, stroke is the second leading cause of death above the age of 60 years, and the fifth leading cause of death in people aged 15 to 59 years old. Europe averages approximately 650,000 stroke deaths each year, while the U.S. has more than 140 000 deaths yearly [14].
Stroke is the second leading cause of disability, after dementia, and disabilities may include loss

of vision and/or speech, paralysis and confusion. Disability as a result of stroke affects 75% of stroke survivors enough to decrease their employability.
Regarding risk factors, high blood pressure contributes to more than 12.7 million strokes worldwide and smoking doubles the risk of ischemic stroke. However, 90% of strokes are preventable, if the risk factors are managed appropriately [14].
Ischemic stroke represents about 85% of all stroke incidents, while hemorrhagic stroke represents only 15% of cases [14].
In Portugal, stroke is the leading cause of death, with more than 30% of deaths happening due to this disease, which represents more than 12 500 people [15].

2.2 Stroke Rehabilitation

2.2.1 Definition

Stroke rehabilitation is a crucial part of the process of stroke recovery. Its purpose consists of re-teaching everyday activities to post-stroke patients who lost those capacities due to stroke, but it also aims at preventing secondary complications and educating friends and family members to have a supportive and moralizing role. This kind of rehabilitation requires multidisciplinary teams, since it involves staff with different skills in cooperation [16].
In stroke rehabilitation, the main focus is to reduce brain injury and promote maximum patient recovery. Therefore, and as previously mentioned, fast detection of a stroke and appropriate emergency medical care are crucial for improving health results [16].
In general, patients who have suffered a stroke are admitted to a stroke unit, which is a ward or dedicated area in the hospital staffed by stroke specialists, where they are subject to specialized medical and surgical care aimed at stabilizing the patient's medical condition. There, patients undergo standardized assessments, such as physical examinations and medical history analysis, in order to help in creating a fit care plan [16].
From there, and once their condition is stabilized, the main goal is rehabilitation, from which patients may be transferred to in-patient services, while others are transferred to out-patient programs or home-based care, according to their status [16]. In-patient programs normally include physicians, nurses, psychologists and several types of therapists, most importantly physical therapists, occupational therapists and speech-language therapists [2]. The primary objectives here are minimizing impairments, achieving functional independency in ADLs and preventing secondary health problems [16].
Lastly, in later phases, patients participate in secondary prevention programs, since there is a higher risk of suffering another stroke, and the patient's primary care provider conducts routine consultations for follow-up [16].
Stroke patients should be mobilized to a stroke unit as early as possible and their rehabilitation should start immediately, preferably within the first 48 hours. Overall, rehabilitation may last from a few days to over a year, where most of the improvement is seen in the first few months and

where after six months, the window of improvement may start decreasing [2], as can be seen in Figure 2.2.
In the following sections, there will be a focus on stroke rehabilitation techniques practiced nowadays and on several guidelines and recommendations for standardizing stroke treatment and recovery.

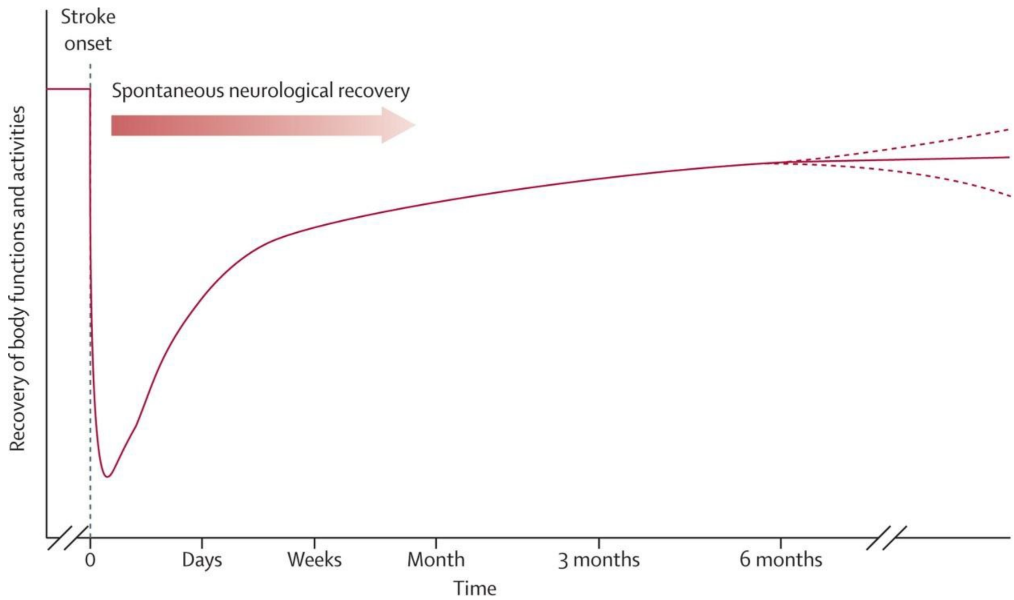

Figure 2.2: Pattern of functional motor recovery for a patient after stroke subjected to an effective therapy [2]

2.2.2 Guidelines

Nowadays, there are several stroke rehabilitation guidelines in practice, on which this section will be based. These guidelines result from an effort of several associations and federations in standardizing clinical practice in stroke rehabilitation.

2.2.2.1 Organization of Services

In general, stroke patients should be admitted to a hospital stroke unit composed by a coordinated multidisciplinary team focused in stroke care. However, in exceptional circumstances, if admission to a stroke unit is not possible, the patient should be enrolled in a generic rehabilitation ward on an individual basis [17].

2.2.2.2 Management Strategies

Physical Therapy

When the goal of treatment is to improve functional ambulation, gait-oriented physical fitness should be provided to all patients considered medically stable and functionally safe to participate.

The use of treadmills is considered an advantageous tool to improve gait speed on patients capable of independently walk at the start of the treatment and the intensity of gait therapy should be improved at all times, when considered safe. One key aspect of physical therapy is task training by repetition, when appropriate for the patient, for either gait speed, walking distance, functional ambulation or sit-stand movements. All stroke patients should be screened for visual problems, and referred appropriately [17].
One very common risk is the development of shoulder subluxation, which should be addressed by applying electrical stimulation to the supraspinatus and deltoid muscles. Patients should be asked about their pain and assessments should be conducted, using validated tools. Given the complexity of post-stroke shoulder pain, the use of flux diagrams or algorithms of behavior is recommended, in which the caregiver follows certain steps relatively to previous ones. Physiotherapists should select interventions according to the patient need, instead of merely focusing on one set of limited practices [17].

Occupational Therapy
Personal ADL training by occupational therapists is recommended as part of an in-patient stroke rehabilitation program [18].
Ongoing monitoring of nutritional status after a stroke should include biochemical measures, swallowing status, unintentional weight loss, eating assessment and dependence and nutritional intake [17].
Stroke patients should have a full assessment of their cognitive strengths and weaknesses either when undergoing rehabilitation or when returning to cognitively demanding activities such as driving or work. This cognitive assessment may be conducted by an occupational therapist with expertise in neurological care [19].

2.2.2.3 Multidisciplinary Team

The multidisciplinary team should include appropriate levels of nursing, physical, occupational and speech/language therapy and social work in an effort to actively involve patients, families and carers in the rehabilitation process as early as possible [17].
Throughout the care pathway, the roles and responsibilities of the core multidisciplinary stroke rehabilitation team should be clearly documented and communicated to the person and their family or carer [19]. Members of the core multidisciplinary stroke team should screen the person with stroke for a range of impairments and disabilities, in order to inform and direct further assessment and treatment [17].

Physicians
Physicians have the primary responsibility for managing and coordinating the long-term care of stroke survivors, including recommending which rehabilitation programs will best address individual needs. Physicians are also responsible for caring for the stroke survivor's general health and for providing guidance aimed at preventing a second stroke, such as controlling high blood

pressure or diabetes and eliminating risk factors such as cigarette smoking, excessive weight, a high-cholesterol diet, and high alcohol consumption [17].

Physical Therapists

Physical therapists specialize in treating disabilities related to motor and sensory impairments. They are trained in all aspects of anatomy and physiology related to normal function, with an emphasis on movement. They assess the stroke survivor's strength, endurance, range of motion, gait abnormalities, and sensory deficits to design individualized rehabilitation programs aimed at regaining control over motor functions [17].

Physical therapists help survivors regain the use of stroke-impaired limbs, teach compensatory strategies to reduce the effect of remaining deficits, and establish ongoing exercise programs to help people retain their newly learned skills [18].

Occupational Therapists

Occupational therapists are concerned with improving motor and sensory abilities, and ensuring patient safety in the post-stroke period. They help survivors relearn skills needed for ADLs such as personal grooming, preparing meals, and housecleaning. Therapists can teach some survivors how to adapt to driving and provide on-road training. They often teach people to divide a complex activity into its component parts, practice each part, and then perform the whole sequence of actions [17].

Speech/Language Therapists

Speech-language pathologists help stroke survivors with aphasia relearn how to use language or develop alternative means of communication. They also help people improve their ability to swallow, and they work with patients to develop problem-solving and social skills needed to cope with the after-effects of a stroke [17].

Vocational Therapists

Approximately one-fourth of all strokes occur in people between the ages of 45 and 65. For most people in this age group, returning to work is a major concern. Vocational therapists perform many of the same functions that ordinary career counselors do. They can help people with residual disabilities identify vocational strengths and develop résumés that highlight those strengths. They also can help identify potential employers, assist in specific job searches, and provide referrals to stroke vocational rehabilitation agencies [17].

Vocational therapists frequently act as mediators between employers and employees to negotiate the provision of reasonable accommodations in the workplace [18].

Rehabilitation Nurses

Nurses specializing in rehabilitation help survivors relearn how to carry out the basic activities of daily living. They also educate survivors about routine health care, such as how to follow a

medication schedule, how to care for the skin, how to move out of a bed into a wheelchair, and special needs for people with diabetes. Rehabilitation nurses also work with survivors to reduce risk factors that may lead to a second stroke, and provide training for caregivers.
Nurses are closely involved in helping stroke survivors manage personal care issues, such as bathing and controlling incontinence [18].

2.2.2.4 Evaluation Indexes

Barthel Index
The Barthel Index is an ordinal scale used to measure a patient's current performance in ADLs introduced in 1965, which has been adapted since then to meet more recent requirements. Each performance indicator is given a rating on a scale of 0-10 corresponding to the patient's capacities. Normally this index is obtained through a simple questionnaire, filled by the occupational therapist, after observation. It is generally considered a valid measure of disability [20].
All in all, the Barthel Index takes into account 10 performance indicators which aim at assessing a certain level of independency (normally 0 is "unable" or "fully dependent", 5 is "mildly dependent" and 10 is "fully able" or "independent"). These 10 variables are: feeding, bathing, grooming, dressing, bowel control, bladder control, toilet use, transfers (i.e. from chair to bed), walking and stair climbing [20].

European Stroke Scale
The European Stroke Scale can be used to assess a patient who has recently had a stroke involving the distribution of a middle cerebral artery. This can be used to measure therapeutic efficacy and to match patients for comparison [21].
The parameters involved are: level of consciousness, basic command comprehension, speech, visual field, gaze, facial movement, arm in outstretched position, arm raising, extension of wrist, fingers, leg maintained in position, leg flexing, dorsiflexion of foot and gait [21].
Each parameter is given a rating on a scale of 0-10, 0-8 or 0-4, depending on the importance of each parameter. The parameters are then added with a maximum score of 100 and a minimum score of 0 [21].

Other Indexes
There are several other indexes which have been recently developed to obtain a quantitative analysis of post-stroke patient status. One example is the Stroke Rehabilitation Assessment of Movement Measure (STREAM), which was designed to be used by physical therapists to provide a quantitative assessment of the stroke patient's motor function of the upper and lower limbs. This technique was specifically conceived in order to be as simple as possible to be applied in a clinical environment.

2.2.3 Current Techniques

2.2.3.1 Constraint-Induced Movement Therapy

Constraint-induced movement therapy (CIMT) is a type of rehabilitation therapy which improves upper extremity function in stroke victims by increasing the use of their affected upper limb [22]. CIMT coupled with intensive and varied exercise training has proven to be effective in reducing spasticity and in increasing function of the hemiplegic upper extremity in chronic stroke patients [23].
The main focus of this technique is to combine restraint of the unaffected limb and intensive usage of the affected limb. The restraint may be done by resorting to a sling or triangular bandage, a splint, a half glove or a mitt, depending on the degree of therapy intensity and level of safety ratio. Constraint typically consists of placing the unaffected hand or arm in an immobilized state, which ultimately forces the patient to use the affected limb, which promotes purposeful movements when performing functional tasks [22].
Usually CIMT involves the person wearing the restraining device for 90% of the waking hours and performing structured tasks with the affected limb for 6 hours and 10 days over a 14 day period on recent modified versions [23].
This technique has shown very promising results due to what is called neuroplasticity. Neuroplasticity or brain plasticity refers to changes in neural pathways and synapses due to changes in behavior, environment, neural processes, thinking or emotions, as well as changes resulting from bodily injury. It ultimately means that if one has some kind of brain impairment resulting from some kind of trauma, such as a stroke, it may be reversed if the subject constantly performs tasks that go against that impairment [22].

2.2.3.2 Mental Practice of Action

Mental practice refers to the use of visuo-motor imagery with the purpose of improving motor behavior. This type of imagery triggers a mental process by which an individual rehearses and simulates a given action; hence it requires the use of one's imagination to simulate a task, since the patient no longer has the capacity of performing the specific action [24].
This technique has been used to rehabilitate motor deficits in a variety of neurological disorders, such as a stroke. It has been proved that a combination of mental practice of action and actual practice of action improves balance, strength, function and the use of upper and lower limbs in chronic stroke [24].
The success of mental practice is due to the brain's capacity of mimicking actual movement execution, since it is capable of retaining many of the movement properties in terms of temporal regularities, programming rules and biomechanical constraints [24].

2.2.3.3 Functional Electrical Stimulation

Functional Electrical Stimulation (FES) of the nerves or muscles in the arm or leg is able to cause movement of the weak limb, since it mimics the action of healthy muscles to improve function and aid in retraining weak muscles and normal movement. This may ultimately result in some degree of restoration of movement. By applying electrodes in the area, the FES device delivers a shock to the survivor's muscle, which activates the nerves and makes the muscle move; the brain is then able to recapture and relearn this movement without the stimulation [25].
FES, for instance, is commonly used in foot-drop, a typical gait abnormality that follows stroke, in which the dropping of the forefoot happens as a result of weakness or damage to the common fibular nerve. FES may also be applied in retraining movement in the upper limb, as it has also shown promising results in treatment of shoulder subluxation and reduction of pain [25].

2.2.3.4 Neurodevelopment Treatment

Neurodevelopment Treatment (NDT), also known as Bobath Concept, is vastly applied in patients undergoing stroke rehabilitation. The Bobath Concept is used for patient assessment and treatment regarding their neurological capabilities after stroke and the goal of its application is to promote motor relearning [26].
Postural control is the main target on which patients begin developing their skills when using NDT, since without it, they will be unable to move and function normally. Usually, patients relearn how to control postures and movements in order to progress to more difficult tasks, while being extensively observed by therapists looking for any abnormalities. One very common abnormal movement is when patients resort to typically uninvolved muscles when trying to perform isolated movements of a particular limb. From postural control, patients will be able to work several other rehabilitation goals such as: coordination of movement sequences, movement initiation, optimal body alignment, abnormal tone or muscle weakness [26].
There are two main intervention techniques for NDT therapeutic handling, which are facilitation and activation of key points of control. Therapeutic handling has the purpose of influencing the quality of movement of the patient. Facilitation is a key strategy practiced by therapists which requires sensory information, such as tactile cues through manual contacts and verbal directions, for reinforcement of weak movement patterns and discouragement of overactive or abnormal ones. Key points of control include, in general, parts of the body that are advantageous when facilitating (or inhibiting) movement and posture, which makes it especially important to activate them during rehabilitation with NDT [26].

2.2.3.5 Virtual Reality Therapy

Virtual Reality Therapy has emerged as a new treatment approach in stroke rehabilitation, since it provides the advantage of practicing activities which cannot be practiced in a clinical environment. This kind of therapy can generally be defined as technological interventions that alter properties of the physical world. Furthermore, virtual reality programs may be designed to be more pleasant and interesting than conventional therapy, which encourages a higher number of repetitions and this design is generally considered safe for participants. A great advantage of the application of these technologies is the feedback they offer to the participant, which may correct or confirm whether any aspect of the movement process is right or wrong. Additionally, these strategies have greater availability and a significantly reduced cost than conventional therapy [27].

This type of rehabilitation has originated the term "serious games", where videogames are designed in order to offer challenges and tasks to patients that involve going against their impairments or advising on what to improve. Exergame, short for "exercise game", is a type of serious game specifically targeting physical activity. Some movement-controlled videogames in platforms like Nintendo Wii, Sony Move and Microsoft Kinect have allowed therapists to integrate commercial gaming systems into stroke therapy [27].

2.2.3.6 Drug Therapies

There are several types of drugs that are administrated in stroke rehabilitation, usually with the purpose of addressing specific consequences of stroke, such as spasticity. These drugs may be oral, intrachraneal or under the form of injections or surgery [28].

Oral drugs like diazepam, dantrolene sodium, baclofen, tizanidine, clonidine and gabapentin are used to treat spasticity, or to decrease stretch reflexes. The problem with these medications is the lack of knowledge of how they are metabolically processed and their side effects [28].

The most common intrachraneal medication used is baclofen, morphine sulfate and fentanyl for severe pain due to spasticity. They require the implantation of a pump that delivers drugs directly to the CNS [28].

The repeated administration of injections of botulinum toxin has shown promising results in relaxing the spastic muscle, since they inhibit the release of acetylcholine, a neurotransmitter [28].

Surgical treatment for spasticity includes lengthening or releasing of muscle and tendons and procedures involving bones [28].

2.2.3.7 Conventional Physiotherapy

Physiotherapy is crucial in stroke rehabilitation, since it helps post-stroke stroke patients through the stages of motor re-learning. The stages involved in this process are extensively described in the Brunnstrom Approach: patients start with flaccid paralysis and, as therapy progresses and movement is regained, movement synergies evolve in complexity and variety. Spasticity may then arise and therapy results may worsen, thus leading to a need in spasticity management. If unaddressed, spasticity may result in abnormal resting limb postures, leading to contractures, which may interfere with hand hygiene, dressing, transfers and other ADLs. Therefore, physiotherapy usually focuses on modifying or reducing muscle tone in order to help in managing spasticity [29].

Techniques in conventional physical therapy involve mobilization of the affected limbs in early rehabilitation, such as scapula mobilization, coupled with elongation of the spastic muscle and sustained stretching. Additionally, initial range of motion may be increased through passive man-

ual rhythmic rotation along with the activation of the antagonist muscle in a slow and monitored movement. In order to maintain muscle stretch and provide tone inhibition, splinting may be applied. Stretching and weight-bearing exercises are also crucial and so is strengthening and resistance training [29].
In general, conventional therapy leads to better results when coupled with one or more of the previously explained techniques [29].

2.2.3.8 Other Therapies

There are several other techniques used in stroke rehabilitation, which include mirror therapy, dynamic splinting, robotic therapy, acupuncture and treadmill training.
More recently, there has been some focus on developing stroke rehabilitation measures involving stem cells, specifically bone-marrow derived mesenchymal stem cells.

2.3 Upper Limb

As previously shown, physical therapy in stroke rehabilitation has a great focus on upper-body physiotherapy, specifically the upper limb.
The upper limb or upper extremity refers to the region of the body from the deltoid area to the hand, which includes the shoulder, axilla, arm and forearm.

2.3.1 Joints

Although the anatomy of the upper limb is extremely vast and complex, this section will focus on the joints of the upper limb, without extensively describing the bones, muscles and ligaments involved, since they are the main anatomical component of the upper limb movement in this dissertation.

2.3.1.1 Shoulder and Axilla

The joints in the shoulder region are the sternoclavicular, acromioclavicular, scapulothoracic and glenohumeral [30].
The sternoclavicular joint is of type saddle. This joint occurs between the clavicle and the sternum and and the muscles involved are the sternomastoid, subclavius and trapezius. The acromioclavicular joint is of type plane. This joint occurs between the scapula and the clavicle and has no muscles involved [30].
The scapulothoracic joint is of type plane. This joint occurs between the scapula and the ribs and the muscles involved are levator scapulae, rhomboid minor, rhomboid major, serratus anterior, trapezius and pectoralis minor [30].
The glenohumeral joint, colloquially called shoulder joint, is of type ball-and-socket. This joint occurs between the head of the humerus and the glenoid cavity of the scapula and involves the

pectoralis major, latissimus dorsi, teres major, supraspinatus, infraspinatus, teres minor, subscapularis, coracobrachialis, long and short heads of biceps, brachii and long head of tricep [30].

2.3.1.2 Arm and Forearm

The joints in the arm and foream regions are the radiohumeroulnar (or cubital), the superior and inferior radioulnar and the radiocarpal [30].
The radiohumeroulnar joint, also called elbow joint, is of type hinge. This joint occurs between the trochlea and capitolium of the humerus, the head of the radius and the notch of the ulna and the muscles involved are biceps brachii, coracobrachialis, brachialis, triceps brachii, brachioradialis, anconeus, superficial flexors of forearm and superficial extensors of forearm [30].
The superior and inferior radioulnar joints are both of type plane. These joints occur between the radius and the ulna, one on the superior portions and the other on the inferior portions, and they involve the pronator teres, pronator quadrates, supinator, brachioradialis and biceps muscles [30].
The radiocarpal joint, which is also called wrist joint, is of type ellipsoid. This joint occurs between the radius and the carpal bones and it also involves the flexor carpi radialis, palmaris longus, flexor carpi ulnaris, flexor digitorum superficialis, flexor digitorum profundus, flexor pollicis longus, extensor carpi radialis longus, extensor carpi radialis brevis and extensor digitorum [30].

2.3.1.3 Hand

The joints in the hand are the carpometacarpal and the interphalangeal [30].
The carpometacarpal joints are of type plane, between carpals and metacarpals 2-5, and of type saddle for the carpal and metacarpal of the thumb. All in all, this joint involves the muscles flexor digitorum superficialis, flexor digitorum profundus, lumbricals, extensor indicis, extensor digitorum, palmar interossei and dorsal interossei [30].
The interphalangeal joints are of type hinge. These joints occur between the phalanges and the flexor digitorum superficialis, flexor digitorum profundus, lumbricals and extensor digitorum are the muscles involved [30].

2.3.2 Range of Motion

Range of motion describes the amount of mobility that can be demonstrated in a certain joint. In general, range of motion can be divided in two types: active range of motion and passive range of motion. Active range of motion corresponds to the amount of movement that can be accomplished by contracting the muscles that normally act across a joint. Passive range of motion is the amount of movement that can be accomplished when the structures that meet at the joint are moved by an outside force, for instance when a physiotherapist is moving a patient's forearm towards his arm, surpassing the normal value of range of motion of the elbow joint. Nevertheless, the values of active and passive range of motions are usually about equal [30].
There are several factors that determine the range of motion of a given joint, such as the shape of the articular surfaces of the bones forming the joint, the amount and shape of cartilage covering

those articular surfaces, the strength and location of ligaments and tendons surrounding the joint, the strength and location of the muscles associated with the joint, the amount of fluid in and around the joint, the amount of pain in and around the joint and the amount of use or disuse the joint has received over time. Dislocation and sprains usually affect the range of motion of a joint and so do several complications that arise from stroke, as previously explained [30].
The most important joints when studying the movement of the upper limb are the glenohumeral joint and the radiohumeroulnar joint, since they determine the range of motion of the shoulder, arm and forearm. The following values of range of motion are relative to a point 0^o, which corresponds to the joint in its still and relaxed state – orthostatic position - in each type of movement. Those values were estimated from average body measurements, on which the shoulder-elbow length was estimated at 36,33 centimeters and the elbow-hand length was estimated at 47,49 centimeters [3].

2.3.2.1 Glenohumeral Joint

The glenohumeral joint can produce several types of movement, such as flexion, extension, abduction, adduction, rotation and circumduction. This joint is responsible for the movement of the shoulder and the arm [30].
The shoulder is able to make an elevation of 40^o and a depression of 10^o. It can also make a flexion movement of 20^o and an extension of 15^o [3].
Regarding the arm, it can elevate itself up to 180^o and suffer a depression of 20^o, while its flexion movement may reach 180^o and its extension may reach 60^o. The arm is also able to perform rotation movements of 90^o to the medial side and 20^o to the lateral side [3].

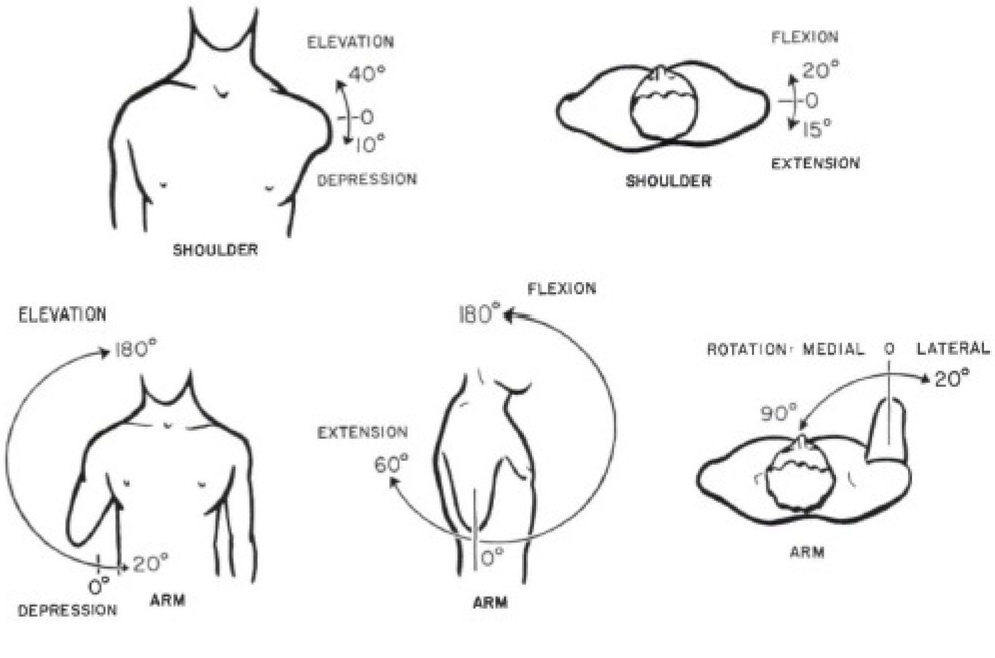

Figure 2.3: Simplified representation of human upper limb movement – shoulder and arm [3]

2.3.2.2 Radiohumeroulnar Joint

The radiohumeroulnar joint is able to move itself through flexion, extension, pronation and supination, since it is a combination of both the humeroulnar joint, responsible for flexion and extension, and the humeroradial joint, that allows pronation and supination. This joint is responsible for the movement of the forearm [30].
The forearm is able to withstand flexions up to 140º, but the extension capacity is close to 0º. Additionally it can perform a supination of 80º and pronation of 90º [3].

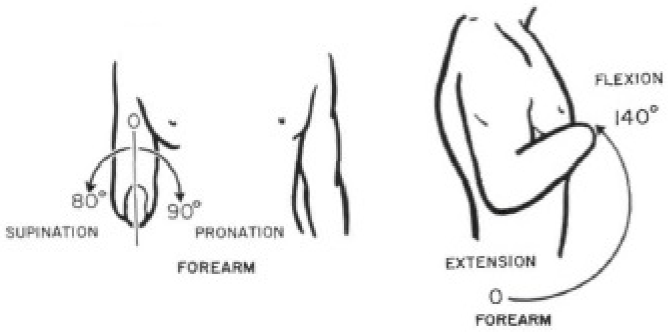

Figure 2.4: Simplified representation of human upper limb movement – forearm [3]

2.4 Mobile Devices and Sensors

2.4.1 Mobile Devices

Mobile devices, such as smartphones and smartwatches, have built-in inertial sensors that are able to make a characterization of human movement. The analysis of human movement is achieved by placing these sensors in specific parts of the body, such as the upper limb, for instance, and having the patient perform certain tasks. These tasks can be tasks that are conducted in stroke therapy, which means that mobile devices can evaluate and offer guidance in a patient's rehabilitation, namely patients with physical impairments in the upper limb as a result of stroke.
From a medical standpoint, this has made fields of study like healthcare and rehabilitation very attractive for the adoption of mobile inertial sensors. The advantages of using mobile devices to evaluate human movement include its low cost sensors, which are less expensive than conventional laboratory equipment like platforms or high-speed cameras; its portability, which avoids laboratory environment restrictions; its small size, enabling free body movements; and the fact that they can be found in several types (smartphones, smartwatches, etc.), models and with different characteristics. Additionally, mobile devices also have the advantage of providing immediate results that do not require complex processing and offer little to no risk to the patient [31]. The recent rise of mobile technology and its inherent advantages has been prompting the creation of new mobile solutions, transforming healthcare mobile devices into a ubiquitous technology [31].
Devices that accurately capture the human movement are a key aspect of physical rehabilitation

systems. These devices enable the acquisition of patient's movements, therefore allowing therapists to remotely study them through quantitative results of movement.
The application of mobile devices is considered a practical and economical approach in the study of movement in humans, when in comparison with others. In healthcare, these devices have been used to monitor human physical activity, evaluate physiological tremors, evaluate posture, identify and classify movements, detect falls in the elderly, among other applications.

2.4.1.1 Smartphone

The new generation of Smartphones is being considered by users as an important personal device, which has been leading to an exponential availability. These devices have an increased potential for an adequate mean of gathering motion data, to use for building human activity prediction systems. The perception of their benefits are becoming commonplace, as users have become accustomed to their ubiquity [32].
As already mentioned, smartphones have their own built-in inertial sensors. These inertial sensors are able to measure changes involving the physical movement of the device in its three axes. In fact, the way these sensors measure these movement changes is directly related to the smartphone's position and orientation: in other words, its reference frame.
The Smartphone Reference Frame (or Device Reference Frame (DRF)) is the standard axis system that is used in the Android API for the accelerometer, the magnetometer and the gyroscope sensors and it is related to how these sensors measure movement. In Figure 2.5 the DRF is shown relative to the smartphone in a vertical position with the screen facing the user.

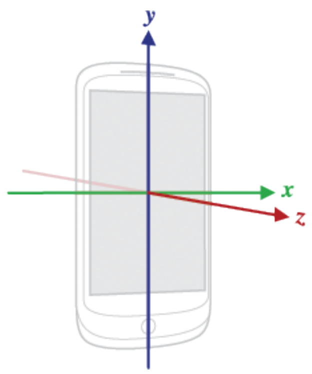

Figure 2.5: Smartphone Reference Frame (retrieved from Sensors Overview of Google Developers API Guides)

2.4.1.2 Smartwatch

The Smartwatch is another type of mobile device that has been receiving attention in recent years with the development of this type of technology. It also has the same built-in inertial sensors as the smartphone and its lightweight structure and small size make it even more portable than other mobile devices.

Although the smartwatch category is still nascent, there is already a wide variety of options on the market that can deliver smartphone notifications, fitness and controller features, mobile applications and more.
The Smartwatch Reference Frame is similar to that of the smartphone. It is depicted in Figure 2.6.

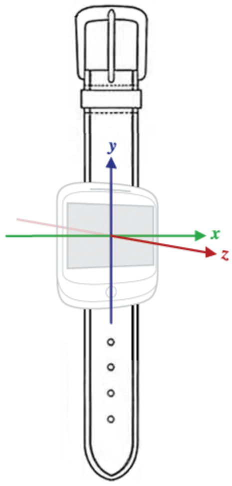

Figure 2.6: Smartwatch Reference Frame (adapted from 2.5)

2.4.2 Sensors

Regarding mobile devices' inertial sensors, there are several aspects that should be considered.
For instance, deciding which type of sensors will be used is of the utmost importance, since different types of sensors offer different types of movement information [33].
Another fundamental question is defining the places and parts of the body where the sensors are placed. One very common solution is applying the sensors in joints of interest, for instance, the ones explained in Section 2.3. Usually, before the procedure, several tests are conducted in order to evaluate the body spots that offer better results, regarding what one intends to study [33].
Lastly, the number of sensors is also determinant to the results of the project. Having an excessive number of sensors may result in difficulties in performing free movements and may lead to a loss of the portability advantage of mobile devices. However, by using less sensors, one may risk not collecting enough sensory data and therefore not being able to recognize the movements properly [33].
Regardless, mobile devices' sensors, although non-invasive, have a certain degree of error mainly due to skin movement, especially if applied in bone prominences, and should always, therefore, undergo a pre-processing step beforehand.

2.4.2.1 Accelerometer

A 3-axis accelerometer sensor gives the acceleration measurements in meters per second squared (m/s^2) along each of the X, Y and Z axes, including the force of gravity. It can be used to recognize the motion activities of the device. The most important source of error of an accelerometer is the bias. The bias of an accelerometer is the offset of its output signal from the true value. It is possible to estimate the bias by measuring the long term average of the accelerometers output when it is not undergoing any acceleration [34].

2.4.2.2 Gyroscope

A gyroscope sensor provides the angular velocities in radians per second (rad/sec) along each one of the three axes. It can be used to obtain the orientation of the device while in motion. If there is a magnetic interference in the surrounding environment, the heading calculated from the magnetometer is not accurate. Moreover, roll and pitch calculated from accelerometer sensor are only accurate when the mobile device is stationary or its acceleration is zero. In this situation, the gyroscope can be used to improve the orientation estimation.
However, the problem with the gyroscope is that there are bias and numerical errors. The bias of a gyroscope is the average output when it is not undergoing any rotation. The gyroscope bias shows itself after integration as an angular drift, increasing linearly over time. Another error arising in gyroscopes is the calibration error, which refers to errors in the scale factors, alignments, and linearities of the gyroscope. Such errors are only observed whilst the device is turning and they lead to the accumulation of additional drift in the integrated signal, the magnitude of which is proportional to the rate and duration of the motions [34].

2.4.2.3 Magnetometer

A magnetometer sensor measures the magnetic field in micro Tesla (μT) in the X, Y and Z axes. It can be used in combination with an accelerometer to find the direction – yaw - with respect to North when the linear acceleration is zero. The main source of measurement errors are magnetic interference in the surrounding environment and in the device [34].

2.5 Machine Learning Technology

Upon receiving sensory data caused by a certain movement of the body, movement characterization follows. In this case, this movement is a result of activities of daily living such as sitting, walking and other general movements.
After signal acquisition, data is pre-processed in order to remove artifacts and noise, improving its reliability. Afterwards, the signal is segmented into its several components by excluding portions of long stillness or interchanging between movements. Since all components that are representative of the movement produced have been computed, it is followed by feature extraction, which allows a quantitative representation of data. Lastly, by applying the extracted features, the algorithm performs a classification step with the purpose of classifying the several movements. The process ends with an evaluation of the algorithm based on performance metrics and comparison with reference data.

Human activity recognition is normally treated as a classification problem, using techniques of machine learning based on probabilistic and statistical reasoning. The basis of machine learning is building a model and a classifier, capable of learning from unseen data. The model represents the data instances and functions of these instances in the training step and ultimately the classifier can generalize for unseen data. Machine learning is a branch of computer science concerned with induction problems for which an underlying model for predictive or descriptive purposes has to be discovered, based on known properties learned from the training data [35].

2.5.1 Feature Generation

The process of transforming a large quantity of data into a set of values that enable movement quantification is called feature generation. These features consist on measurable properties of data that allow quantification and characterization, which facilitates an objective evaluation of movement. Feature generation is a crucial step since features must be thoroughly selected and analyzed so that it is possible to generate relevant information from input data, which will have an essential role in classification [36]. The number of features should not be too large, because of the curse of dimensionality, but should contain enough information to accurately predict the output. The curse of dimensionality refers to a series of complications that arise due to the fact that when the dimensionality increases, the volume of the space increases so fast that the available data become sparse, which is problematic [4].
Sensory data may be analyzed in two domains: time domain and frequency domain [36]. Time-domain features are simple mathematical and statistical metrics used to extract basic signal information from raw data. It could also be calculated as data is being read. Usually, these features are simple to compute. Frequency-domain techniques capture the respective nature of a sensor signal. In order to compute frequency-domain features, the sensor data window has to be transformed into frequency domain, using Fast Fourier Transform (FFT) [32], which is a spectral representation of the signal. In Table 2.1 some commonly generated features from the literature are presented [37, 38].

2.5.2 Feature Selection

There are two main reasons to keep the dimensionality of the feature data as small as possible: measurement cost and classification accuracy. A limited yet salient feature set simplifies both the model representation and the classifiers that are built on the selected representation. Consequently, the resulting classifier will be faster and will use less memory [4].
This means that, from an information processing point of view, adding more features does not always lead to better classification results [39]. This sometimes leads to the necessity of adding feature selection process. Optimal feature selection plays an important role in reducing redundant and irrelevant features that lead to lower classification rates as well as over-fitting when included [40]. There are several feature selection algorithms and in Figure 2.7 there is a brief overview of those made by [4].

Table 2.1: Overview of commonly calculated features

Feature	Description
Mean	Average value of the array
Median	Median value of the array
Variance	Squared difference from the mean value
Standard Deviation	Difference from the mean value
Minimum	Smallest value in array
Maximum	Largest value in array
Range	Difference between maximum and minimum
Root Mean Square	Square root of the mean of the squares
Cross-Correlation	Similarities between data
Zero-Crossing	Changes of signal in array
Interquartile range	Difference between the first and third quartiles
Energy	Average sum of the squares
Entropy	Measurement of signal organization
Skewness	Third moment around the mean value
Kurtosis	Fourth moment around the mean value
Energy band	Energy of a frequency interval
Mean frequency	Average of the frequency signal
Vector angle	Angle between two vectors

2.5.3 Classification

Machine learning algorithms can be divided in three categories: supervised learning, unsupervised learning and semi-supervised learning. Supervised learning refers to the use of labelled data to train an algorithm, which then becomes able to classify unlabelled data. Unsupervised learning is a method which tries to directly build recognition models from unlabelled data by using density estimation methods to discover groups of similar examples in order to create learning models. Semi-supervised learning falls between them, since it uses both labelled and unlabelled data for training a classification model [35].

However, supervised learning is more common in the field of activity recognition. Supervised learning is divided in two phases: training and test. After selecting the classification algorithm, it is run in a training dataset, which is labelled, in order to create a predicitive model. This model will classify or label the unlabeled objects of data in the test dataset and the performance of this classification step will then be evaluated. Some supervised learning algorithms require the user to determine certain control parameters. These parameters may be adjusted by optimizing performance on a subset of the training set, called a validation set, or via cross-validation. The result is a classification function which is then run on a test dataset to evaluate the algorithm performance [35].

After extracting the feature data, a classification of the movements is conducted. At this point, the classification algorithm builds a model for different body movements and applies a classifier in order to identify the ADLs. This means that the choice of the classifier is extremely important

Method	Property	Comments
Exhaustive Search	Evaluate all $\binom{d}{m}$ possible subsets.	Guaranteed to find the optimal subset; not feasible for even moderately large values of m and d.
Branch-and-Bound Search	Uses the well-known branch-and-bound search method; only a fraction of all possible feature subsets need to be enumerated to find the optimal subset.	Guaranteed to find the optimal subset provided the criterion function satisfies the monotonicity property; the worst-case complexity of this algorithm is exponential.
Best Individual Features	Evaluate all the m features individually; select the best m individual features.	Computationally simple; not likely to lead to an optimal subset.
Sequential Forward Selection (SFS)	Select the best single feature and then add one feature at a time which in combination with the selected features maximizes the criterion function.	Once a feature is retained, it cannot be discarded; computationally attractive since to select a subset of size 2, it examines only $(d-1)$ possible subsets.
Sequential Backward Selection (SBS)	Start with all the d features and successively delete one feature at a time.	Once a feature is deleted, it cannot be brought back into the optimal subset; requires more computation than sequential forward selection.
"Plus l-take away r" Selection	First enlarge the feature subset by l features using forward selection and then delete r features using backward selection.	Avoids the problem of feature subset "nesting" encountered in SFS and SBS methods; need to select values of l and $r(l > r)$.
Sequential Forward Floating Search (SFFS) and Sequential Backward Floating Search (SBFS)	A generalization of "plus-l take away-r" method; the values of l and r are determined automatically and updated dynamically.	Provides close to optimal solution at an affordable computational cost.

Figure 2.7: Overview of Feature Selection methods by [4]

and sometimes more than one classifier is applied. There are several types of classification algorithms that may be applied in movement recognition: lazy methods (such as k-nearest neighbors), decision tree learners (like C4.5), Bayesian methods (as in Naive Bayes or Bayesian nets) and function-based learners (such as support vector machine) [41].

2.5.3.1 k-Nearest Neighbors

In the k-Nearest Neighbors (k-NN) algorithm, the class assigned to a vector x is the class with the maximum number of votes coming from the k samples nearest to x. These classifiers are memory-based and do not require a model to fit. To find the closest samples the algorithm can use the Euclidean distance. The majority class of the k closest neighbors found is assigned to the test instance. It is a fast algorithm and the complexity is independent of the number of classes [35, 41].

2.5.3.2 Decision Tree

Decision trees use a tree in which for each attribute, one branch per each possible result of a test is generated. The algorithm stops when it finds a leaf, that represent a class [41], and uses a divide-and-conquer approach.

2.5.3.3 Bayesian classifiers

For Bayesian classifiers, when an object is erroneously classified it can be quantified as a cost or a loss. The expectation of the cost can be used as an optimization classifier [35, 41]. This algorithm represents the probability distributions of the training data.

2.5.3.4 Support Vector Machine

Support Vector Machine (SVM) are linear classifiers that locate a separating hyperplane in the class space and classify points in that space. The objective is to find the maximum margin hyperplane separating two classes. The instances with minimum distance to the hyperplane are defined as support vectors. The computational cost increases as one wants to separate more classes. It defines the kernel function, which plays the role of the dot product in the class space [35, 41].

2.5.4 Evaluation

After the classification step is complete, there is a need to evaluate the performance of the activity recognition algorithm. There are different ways to evaluate the performance of an activity recognition algorithm, but all the performance metrics usually revolve around the confusion matrix. When dealing with a multi-class problem, where each activity represents one class, the classification results can be represented in an *n-n* matrix of *n* classes, which is the confusion matrix. In this matrix, the columns usually represent the model prediction or test outcome, that is the class result of the model; the rows represent the ground truth or gold standard, that is the actual true class. In Figure 2.8 there is depicted an example of a confusion matrix with two classes with the designation of each cell result: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) [5].

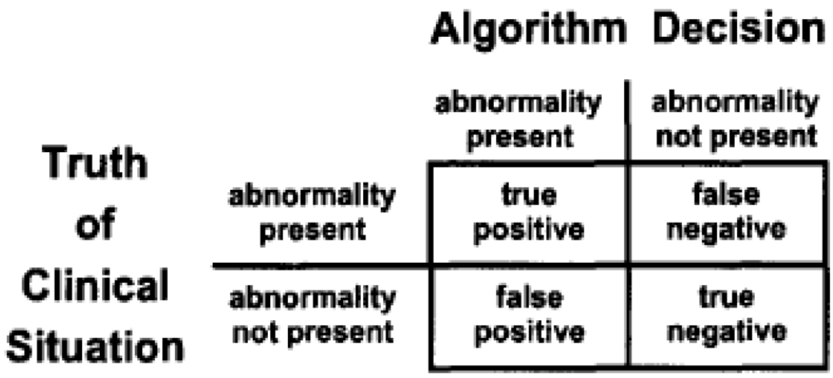

Figure 2.8: Example of a confusion matrix with two classes - Present and Not Present [5]

From the confusion matrix, it is possible to estimate a series of performance metrics, each one with a different meaning and importance, as a means of evaluating the algorithm. Those are organized in Table 2.2 along with its calculation formula.

Table 2.2: Performance metrics for algorithm evaluation and its calculation formulas [5]

Metric	**Formula**
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
Precision	$\frac{TP}{TP+FP}$
Negative Predictive Value	$\frac{TN}{TN+FN}$
Fall-out	$\frac{FP}{TN+FP}$
Miss Rate	$\frac{FN}{TP+FN}$
False Discovery Rate	$\frac{FP}{TP+FP}$
Accuracy	$\frac{TP+TN}{TP+FP+TN+FN}$
F-measure	$\frac{2*Precision*Sensitivity}{Precision+Sensitivity}$

The Sensitivity (or True Positive Rate, or Recall) measures the proportion of positives that are true positives and the Specificity (or True Negative Rate) measures the proportion of negatives that are true negatives. The Precision (or Positive Predictive Value) measures the proportion of supposed positives that are true positives and the Negative Predictive Value measures the proportion of supposed negatives that are true negatives. The Fall-out (or False Positive Rate) measures the proportion of negatives that are false positives and the Miss Rate (or False Negative Rate) measures the proportion of positives that are false negatives. The False Discovery Rate measures the proportion of supposed positives that are false positives. The Accuracy measures the capacity of the algorithm to correctly detect classes. The F-measure combines precision and sensitivity by their harmonic mean [5].

There is also another algorithm evaluation technique which is the Receiver Operating Characteristic (ROC) curve, a graphical plot that illustrates the performance of a binary classifier system. This curve is created by plotting the True Positive Rate against the False Positive Rate. The ROC-curve offers a visual representation of the algorithm's performance, which is as good as the proximity between the vertex of the curve and the top left hand corner of the graph. The ROC-curve also enables the calculation of the Area Under Curve (AUC), another performance metric. The algorithm's performance is maximum if the AUC equals 1 and minimum if it equals 0 [5]. An example of two ROC-curves is shown in Figure 2.9.

2.5.5 Related Work

Virtual reality therapy and conventional physiotherapy, both described in Section 2.2, are two fields of stroke rehabilitation that are very prone to the application of techniques like the ones described in this section. The quantitative data provided by those techniques can be applied to virtual reality therapy in the form of performance metrics and visual input of the rehabilitation status. Moreover, human movement recognition devices are able to inform the physical therapist if the activity being performed by the stroke patient is close to the correct way it should be performed.

The importance of classification of ADLs is very broad. For therapists, it is extremely useful to have devices that are able to assist them in conducting rehabilitation and that offer quantified

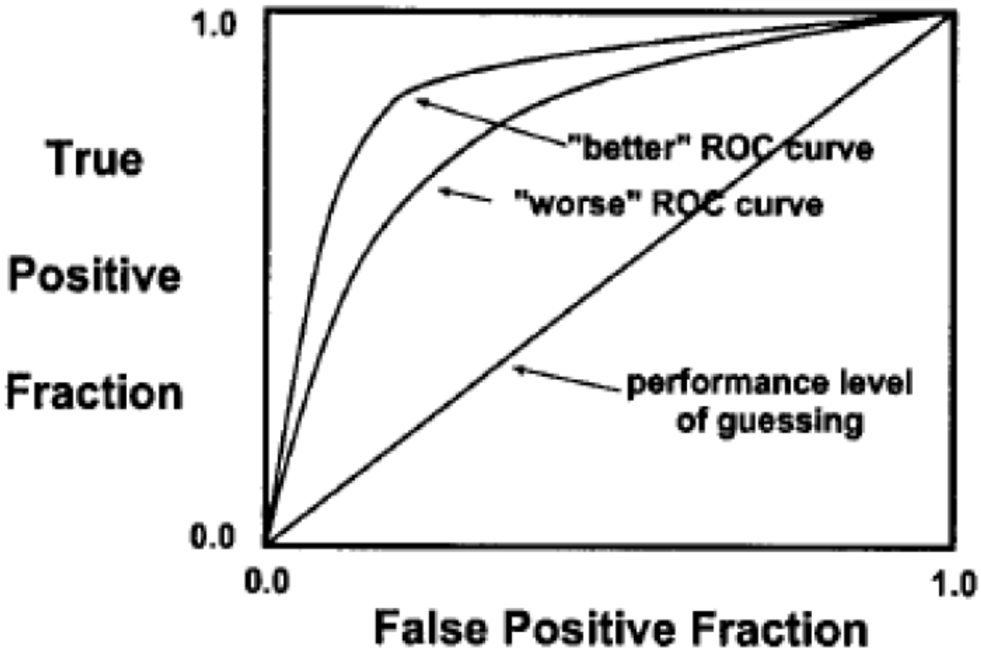

Figure 2.9: Example of two ROC-curves [5]

information about the patient status. As a consequence, the choice of which features to extract and how they are extracted is of the utmost importance, as previously demonstrated, and so is the classifier that is chosen by the developer.
In Table 2.3 there is an overview of activity recognition related work by several authors [42-51]. The table is organized in terms of authors, date, devices and sensors, detected activities, features used, classifier and algorithm accuracy.

Table 2.3: Overview of activity recognition related work

Author	Year	Devices and Sensors	Sensor Location	Activities	Features	Classifier	Accuracy
Aguiar et al.[42]	2014	Accelerometer Android Smartphone	Front Pocket	Running Walking Laying	mean, median, max, min, rms, std, median dev, iqr, energy, entropy, skewness, kurtosis	Decision Tree	99,50%
Anjum et al.[43]	2013	Accelerometer	Hand Front Pocket Shirt Pocket Handbag	Walking Running Upstairs Downstairs Driving Cycling	mean, std, magnitude of acc cross-axis correlation, spectral energy frequency domain entropy	Naive Bayes KNN SVM Decision Tree	95,20%
Bento et al.[44]	2012	MARG sensors	Shoulder Elbow Wrist	Elbow extension Arm rotation Arm pronation	N/A	Decision Tree	N/A
Khan et al.[45]	2010	Accelerometer SCH-M490 Smartphone	Front Pocket Rear Pocket Shirt Pocket	Walking Running Downstairs Upstairs	AR-coeffiecients, SMA	ANN	96%
Atallah et al.[46]	2009	Accelerometer Ambient sensors	Ear Ambient	Walking Reading Preparing food	variance	Naive Bayes	70,20%
Jin et al.[47]	2009	Accelerometer	Waist	Running Still Jumping Walking	DCT, DCT magnitude	SVM	95,03%
Saponas et al.[48]	2008	iPhone Accelerometer Nike+iPod Sports Kit	Front Pocket	Running Walking Cycling Sitting	mean, std, min, max, energy	Naive Bayes	97%
Hong et al.[49]	2008	Accelerometer HTC Smartphone	Wrist Stomach Knee	Sitting Standing Walking Lying Running	mean, energy, entropy, correlation	Decision Tree	93,79%
He et al.[50]	2007	Accelerometer	Chest Thighs	Standing Sitting Falling Lying	mean, max, min	HMM	95,82%
Parkka et al.[51]	2006	Accelerometer Gyroscope GPS Physiological sensors	Wrist Chest Forehead Hand Ambient	Walking Running Cycling Rowing Lying	mean, variance, median, skewness, kurtosis, spectral centroid, spectral spread, frequency peak, signal power	Decision Tree ANN	84%

Chapter 3

Algorithm Development

This chapter describes the development of an algorithm that is intended to be used in stroke rehabilitation, as well as its implementation. Firstly there is a brief introduction where the several devices and its sensors are explained, namely their capabilities, limitations and application in spatial orientation. Afterwards, the movements that are intended to be recognized are mentioned and contextualized in terms of impact and importance in stroke rehabilitation. To conclude, there is an extensive description of the developed algorithm and each of its several components. The algorithms for both movements that were selected will be explained in detail and the final results of the development will be clearly demonstrated.

3.1 Introduction

3.1.1 Devices

3.1.1.1 Smartphone

In this project, two different smartphones were used for acquiring signal. These were the Samsung Galaxy Nexus and the Motorola Moto G (2nd generation), both running Android operating system.

The Samsung Galaxy Nexus was released in November 2011. It weights 135 grams and its dimensions are 135.5 x 67.9 x 8.9 millimeters. It is equipped with a 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer, among other sensors. It has a removable Li-Ion 1750 mAh battery which has a battery life of 31 hours[1]. The price range is 180 euros.

The Motorola Moto G (2nd gen) was released in September 2014. It weights 149 grams and its dimensions are 141.5 x 70.7 x 11 millimeters. It is equipped with a 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer, among other sensors. It has a non-removable Li-Ion 2070 mAh battery which has a battery life of 50 hours[1]. The price range is 180 euros.

[1] means that you'll need to fully charge the device in question once every the specified number of hours if you do one hour of 3G calls, one hour of video playback and one hour of web browsing daily

3.1.1.2 Smartwatch

The smartwatch used in this project was the LG G Watch (W100). This device was released in June 2014 and runs the Android Wear operating system. It weights 63 grams and its dimensions are 37.9 x 46.5 x 9.95 millimeters. It is equipped with a 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer. It has a 400mAh battery which has a battery life of 36 hours. the price range is 210 euros.

3.1.2 Sensors

Although there are several inertial sensors available in smartphones and smartwatches, during the project there was an effort towards using the minimum number of sensors possible to detect the movements. This enabled the algorithm to be computationally less expensive, since only the required sensors were running, which decreases battery consumption.
In Table 3.1 the sensor technical specifications are displayed for each of the mobile device's inertial sensor.

Table 3.1: Sensor technical specifications for each mobile device

Device	Sensor Name	Sampling Rate
Motorola Moto G 2nd Gen	Bosch BMC 150 Accelerometer	100 Hz
	Bosch Gyroscope	100 Hz
	Bosch BMC 150 Magnetometer	20 Hz
Samsung Galaxy Nexus	Invensense MPL Accelerometer	100 Hz
	Invensense MPL Gyroscope	100 Hz
	Invensense MPL Magnetometer	100 Hz
LG G Watch (W100)	STMicroelectronics LGE Accelerometer	35 Hz
	STMicroelectronics LGE Gyroscope	35 Hz
	AKM LGE Magnetometer	35 Hz

3.1.3 Movements

In order to decide which movements would be detected by the algorithm, a meeting was held with a stroke physiotherapist at the *Centro de Reabilitação Profissional de Gaia* (CRPG), an occupational therapy center in Porto which works with stroke patients. According to the physiotherapist, from her experience, an upper limb movement that is frequently lost or severely impaired is the eating movement. This movement consists of taking a piece of flatware, namely a spoon or a fork, from the plate to one's mouth using the upper limb. Patients usually lose the ability of performing this movement, which leads to a lack of functional independence on a daily basis.
Additionally, as stated by the stroke physiotherapist, stroke victims also have a tendency to remain inactive during the day. In fact, she said that detecting the number of times a person stood up and the time that person was standing were useful metrics for a stroke physiotherapist to know a patient idleness during the day. Therefore, a second movement was identified, which was the

sitting and standing movements.
Movement recognition algorithms can be broadly divided into two major strands. The first strand uses machine learning techniques based on probabilistic and statistical reasoning while the second strand of algorithms is based on logical modelling and reasoning [41]. In this project, both approaches were used.

3.1.3.1 Sitting and Standing

The sitting and standing movements were detected using the smartphones. These devices were placed inside the front pocket of the patient's trousers. Their low weight and medium dimensions make them comfortabe to be used on a daily basis. In this project, two smartphones were used in order to compare results from different devices, although one smartphone is enough to detect the sitting and standing movements.

3.1.3.2 Eating

The eating movement was detected using the smartwatch. This device was placed on the patient's wrist, similarly to an ordinary wristwatch. Its minimal weight and size allows for this device to be used without interfering in the daily activity of the patient.

3.1.4 System Architecture for Algorithm Development

In this chapter, as will be explained in extensive detail in the following sections, the full process of movement analysis is made offline. The aim is to study the different detection methods which can be applied in the development of the movement-detection algorithm so that it can be applied in the exergame afterwards. Therefore, there is no urgent need in this phase to implement the methods in real-time. Nevertheless, since the final purpose is to function in real-time, there is an effort in implementing methods that are not computationally expensive and do not spend excessive system memory.
In Figure 3.1 there is a general diagram depicting the full architecture of the system in this development phase.
The three inertial sensors explained before are already integrated on both mobile devices and these are worn by the user according to the instructions mentioned previously.
The dataset is collected outside of the movement-detection algorithm in the form of comma-separated text files with the following organization: sensor id (which can be A, G or M), timestamp (in nanoseconds), X-axis value, Y-axis value, Z-axis value.
These files are then loaded into the IDE and the information of each text-file component - sensor id, timestamps and axes values - is stored to be accessed in further phases.
This information is then visualized in order to obtain detection euristics for the movement detection algorithm (explained in full detail in the following sections) which is divided in two parts: the sitting/standing detection and the eating detection. For the sitting/standing detection, a set of two thresholds appeared to be a good process of division of the signals fractions in time, corresponding

to the movement phases. These thresholds were validated on the basis of an error calculation relative to the actual annotations of the movement files. For the eating detection, the signals were first inspected and, since simple thresholds were not capable of discriminating eating and not-eating movements, more complex classification methods were necessary. The signals were then segmented according to the variation of the best detector, which was the gyroscope, when compared with a single threshold. The resulting segmentation was validated in a similar way as the sitting/-standing thresholds. The segments were then used to feed several pattern recognition methods, as explained below, in order to discrimiate eating from not-eating movements.

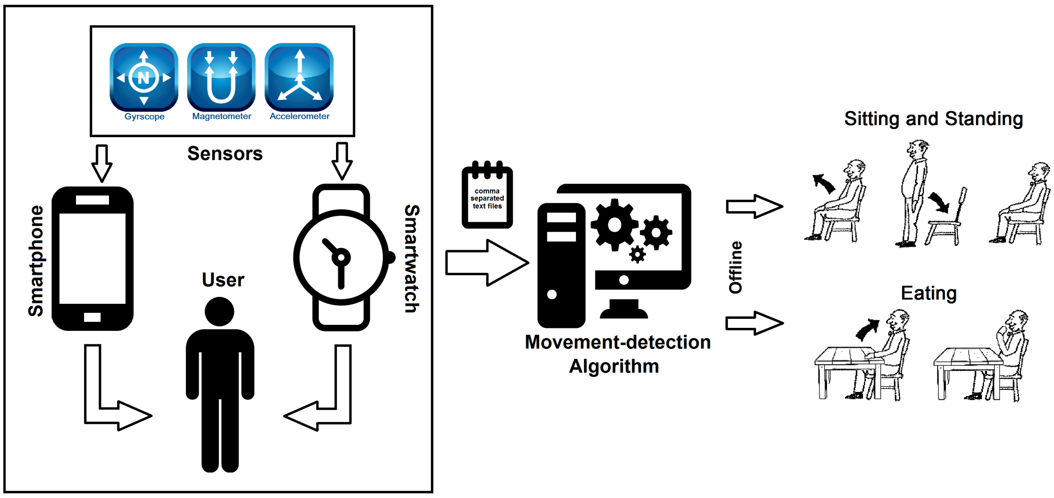

Figure 3.1: Diagram depicting the system architecture

3.2 Sitting and Standing

As mentioned previously, there was an effort towards using the minimum number of sensors possible to detect the movements. To detect sitting and standing movements, the algorithm only uses accelerometer data. In this part of the project, a threshold-based approach was used, which was applied to the raw data of the 3-axis accelerometer.
The diagram in Figure 3.2 shows an overview of the sitting and standing movement detection algorithm. This algorithm is composed by four different components - Signal Acquisition, Signal Pre-Processing, Movement Detection and Evaluation - which will be thoroughly explained in the following sections.
The whole algorithm was developed using the Eclipse IDE and was written in Java.

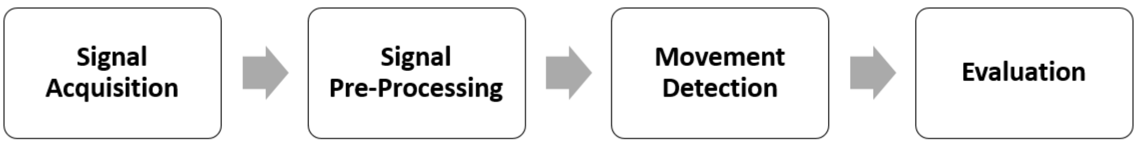

Figure 3.2: Process diagram depicting the overall sitting and standing detection algorithm

3.2.1 Signal Acquisition

On a first stage, in order to visually analyze the accelerometer raw signal, a small dataset of 8 individuals was collected among fellow colleagues. This dataset collection consisted on the individuals starting on the sit position and performing 6 sit-to-stand-to-sit transitions. In Figure 3.3 it is depicted the sitting and standing movements performed by the individuals in the dataset collection. Afterwards, a second dataset was collected from 6 elderly individuals, which was added to the previous one. These individuals performed the same series of movements as the previous dataset collection.
Lastly, in order to fully validate the developed algorithm, a final dataset was collected comprising 12 elderly individuals.
All the demographic information regarding the individuals involved in the three dataset collections is depicted in Appendix A.

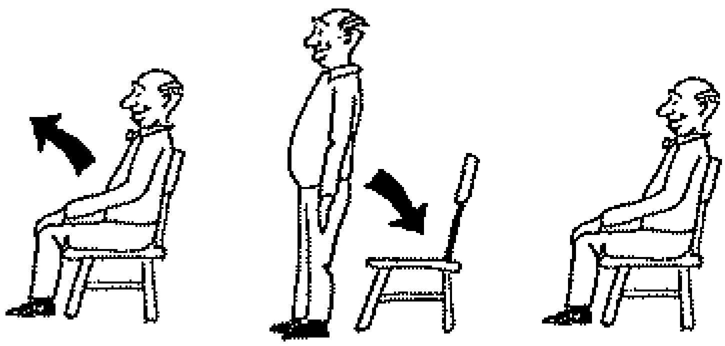

Figure 3.3: Schematic of the sit-to-stand-to-sit movement

The data recording application used in the smartphone had already been developed by FhP-AICOS and was the one used in the dataset collection. This application enables the user to create a profile and select the place where the smartphone will be used. It also allows several sensors from the smartphone to be selected and recorded. In this case, the smartphones were placed in the front pocket, one on the right and the other on the left, and the selected sensors were the accelerometer. The recording process of the smartphone recording application is shown in Figure 3.4.

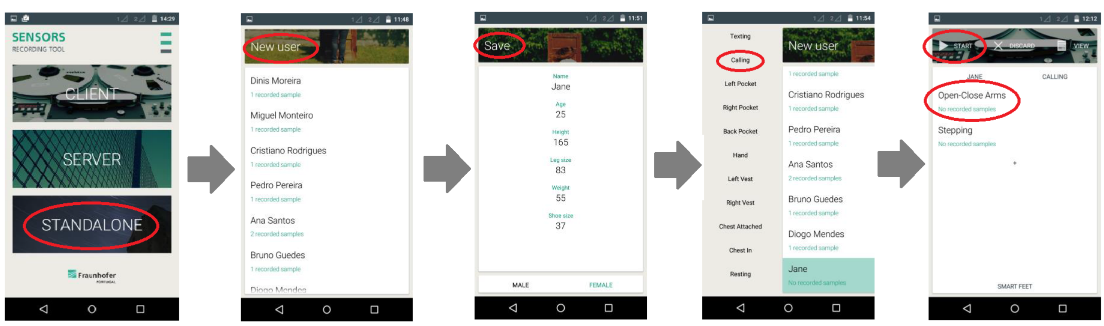

Figure 3.4: Example of the data recording application developed by FhP-AICOS - the red circle represents the selected option

3.2.2 Signal Pre-Processing

Since the accelerometer is very sensible to movement, a low-pass filter was applied in order to remove noise and smooth the signal. The applied filter was a Weighted Moving Average filter with a window size of 30 samples. This filter scans each value of accelerometer data and calculates the sliding weighted average using a specified window size, in this case 30. This type of filter has already been used in previous work for noise removal [52]. This calculation gives a progressively higher weight to the more recent values, as shown in Equation 3.1.

$$WeightedAverage = \frac{3s_i + 2s_{i-1} + 1s_{i-2}}{6} \tag{3.1}$$

3.2.3 Movement Detection

In order to detect the sitting and standing movements, a threshold-based approach was applied. The threshold-based approach was studied from the filtered accelerometer signals obtained with the first dataset. The thresholds were progressively corrected and improved upon receiving the second dataset. This approach allowed to obtain more insight about accelerometer signals during both movements and to detect potential features to discriminate both activities. The process employed was based in signals supervision and also in literature review.
One requirement for this part of the algorithm was that the user should be able to use the smartphone in several positions inside the front pocket, since it is intended to be used in daily routine which is an uncontrolled environment. Thus there was a need to compute a feature that was invariant regardless of the smartphone position. Firstly, eight types of smartphone positions were identified, which were: screen up/phone up, screen down/phone up, screen right/phone up, screen left/phone up, screen up/phone down, screen down/phone down, screen right/phone down, screen left/phone down. These positions are identified in Figure 3.5.

This means that there are essentially two position problems to solve: the screen's position and the phone's position.

3.2.3.1 Position Issues

Screen Position
Starting with the problem of the screen's position, there are four different options: up, down, right and left. For explanation purposes, it will be assumed phone position up.
By reviewing Figure 2.5, it is possible to conclude that during the sitting and standing movements, the smartphone's accelerometer values change considerably in only two of its three axes. In sitting position, the smartphone is horizontal, which means that if the user changes to the standing position, the smartphone will be vertical.
If the smartphone is screen up during this movement, the acceleration values will vary as so: X-axis will be equal, Y-axis will vary from approximately 0 m/s^2 to approximately -10 m/s^2 and Z-axis will vary from approximately 10 m/s^2 to approximately 0 m/s^2. On the other hand, if the smartphone is screen down during this movement, the acceleration values will vary as so: X-axis

Figure 3.5: Eight possible smartphone positions inside the front pocket

will still be equal, Y-axis will still vary from approximately 0 m/s^2 to approximately -10 m/s^2, but Z-axis will vary from approximately -10 m/s^2 to approximately 0 m/s^2.

If we change the screen position from up or down to right or left, the variations will be the same, only the X-axis will be replaced with the Z-axis. This means that the Y-axis is invariant in terms of screen position, so we can conclude that the Y-axis accelerometer value is a feature that may be considered accurate for detecting the sitting and standing movements.

Phone Position

However, the phone's position is still an issue, since the Y-axis accelerometer value is not invariant in this case. To illustrate this, we will suppose that the screen position is up.

For the same movement explained above, if the smartphone is phone up, the acceleration values will vary as so: X-axis will be equal, Y-axis will vary from approximately 0 m/s^2 to approximately -10 m/s^2 and Z-axis will vary from approximately 10 m/s^2 to approximately 0 m/s^2, as we had already seen. Nonetheless, if the smartphone is phone down during this movement, the acceleration values will vary as so: X-axis will still be equal, Y-axis will vary from approximately 0 m/s^2 to approximately 10 m/s^2 and Z-axis will vary from approximately 10 m/s^2 to approximately 0 m/s^2. Hence, the Y-axis in not invariant. It is possible to solve this problem by having the algorithm compute the absolute value of the Y-axis accelerometer, which then makes it invariant in terms of phone position.

Therefore, the feature that is used to detect the sitting and standing movements is the absolute value of the Y-axis accelerometer value. Although we only analyzed the standing movement, the variations of acceleration for the sitting movement are the same, but with the values switched.
In Table 3.2 there is an overview of the variations of the acceleration values in terms of screen and phone positions, for the standing movement.

Table 3.2: Variations of acceleration for each screen and phone position in the standing movement

Screen Position	**Phone Position**	X-axis (m/s^2)	Y-axis (m/s^2)	Z-axis (m/s^2)
Up	**Up**	equal	0 to -10	10 to 0
Down	**Up**	equal	0 to -10	-10 to 0
Right	**Up**	-10 to 0	0 to -10	equal
Left	**Up**	10 to 0	0 to -10	equal
Up	**Down**	equal	0 to 10	10 to 0
Down	**Down**	equal	0 to 10	-10 to 0
Right	**Down**	-10 to 0	0 to 10	equal
Left	**Down**	10 to 0	0 to 10	equal

3.2.3.2 Thresholds

Once it is understood how phone and screen positions affect acceleration values, there is a need to define the thresholds that will be applied to the algorithm in order to correctly detect sitting and standing. To define those, one needs to perceive how these two movements affect the smartphone orientation in the pocket and how that orientation changes the absolute value of the Y-axis acceleration.
For instance, supposing a standing movement with the smartphone in screen up/phone up position, the user starts in sitting position and finishes in standing position, which means the smartphone changes from horizontal to vertical position. This means that the Y-axis acceleration changes from approximately 0 m/s^2 to approximately -10 m/s^2. On the other hand, for the sitting movement, the smartphone changes from vertical to horizontal position, which means an opposite variation of the Y-axis acceleration value: from approximately -10 m/s^2 to approximately 0 m/s^2.
Regarding the thresholds, they were defined based on direct observations of movement patterns in the individuals of the first dataset. Moreover, the thresholds were defined at:

- **Sitting** - less than 2 m/s^2
- **In Transition** - between 2 m/s^2 and 8 m/s^2
- **Standing** - more than 8 m/s^2

These thresholds were defined as the ones with the best results based on a minimization of the associated measurement error. Further details about this are explained below.

3.2.3.3 Quantitative Metrics

There were several metrics that were calculated by the algorithm. Those were:

- Total time standing
- Total time sitting
- Number of transitions

3.2.4 Evaluation

The final step of the sitting and standing detection part of the algorithm was the evaluation phase. In this phase, performance metrics were calculated for the several metrics that were computed in the previous section.
The following performance metrics were computed:

- Mean Relative Error
- Mean Absolute Error

Both the mean relative error and the mean absolute error were calculated by using a stopwatch to measure the real time the dataset subjects were standing and sitting. This real time was then compared with the total time standing and total time sitting computed by the algorithm.

3.3 Eating

For the eating movement, a more complex algorithm was designed, which used machine learning techniques. This algorithm uses the three sensors (accelerometer, gyroscope and magnetometer) to extract features and classify the different activities, in this case the eating and not-eating movements.
The diagram in Figure 3.6 shows an overview of the eating movement detection algorithm. This algorithm is composed by seven different components - Signal Acquisition, Signal Pre-Processing, Signal Segmentation, Feature Generation, Feature Selection, Classification and Evaluation - which will be thoroughly explained in the following sections.
The first four components of the algorithm were developed using the Eclipse IDE and were written in Java, while the last three were developed using RapidMiner.

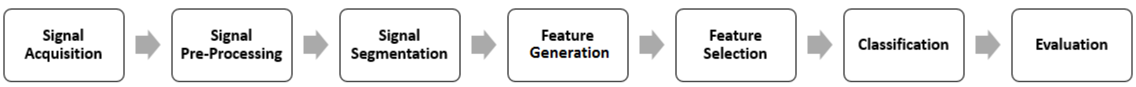

Figure 3.6: Process diagram depicting the overall eating detection algorithm

3.3.1 Signal Acquisition

Similarly to the sitting and standing movements, on a first stage, in order to visually analyze the raw signal, a small dataset of 8 individuals was collected among fellow colleagues. This dataset collection consisted on the individuals starting on the sit position in front of a table and performing 10 eating movements followed by 10 false eating movements, which only reached half of the way to the mouth. A true eating movement consisted only in the hand moving from the table to the mouth. The hand movement back to the table was not considered, although it was recorded. In Figure 3.7 it is depicted the eating movements performed by the individuals in the dataset collection. Afterwards, a second dataset was collected from the same 6 elderly individuals, which was added to the previous one. These individuals performed the same series of movements as the previous dataset collection.
Lastly, in order to fully validate the developed algorithm, a final dataset was collected comprising 12 elderly individuals.
The individuals involved in the dataset collection for the eating movement were the same as the sitting and standing movements, thus all the demographic information regarding the individuals involved in the three dataset collections is also depicted in Appendix A.

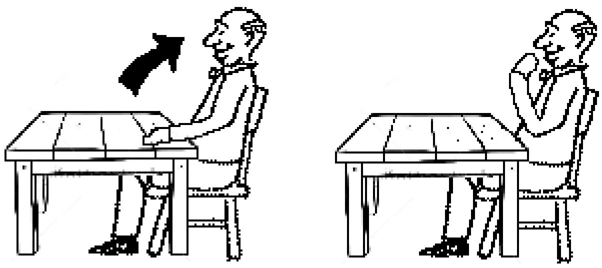

Figure 3.7: Schematic of the eating movement

3.3.2 Signal Pre-Processing

Similarly to the sitting and standing movement detection, a low-pass filter was applied in order to remove noise and smooth the signal. The applied filter was also a Weighted Moving Average filter with a window size of 30 samples.
In parallel with the eating movement detection, the algorithm also computed another metric, which was the active time. This metric was calculated as a result of the advice from the physiotherapist of CRPG, who said that any activity performed by the stroke patient should be considered and reported to the physiotherapist, giving the fact that these patients usually develop seriously idle routines.
To compute this metric, the raw accelerometer X-axis signal was filtered with a 1st-order Butterworth High-Pass filter with a cutoff frequency of 1Hz. This filter was applied in order to normalize accelerometer magnitude signal baseline and apply a threshold. The signal's absolute value was computed and the threshold was defined at 0,5 m/s^2, above which the user was considered in

movement and the time was recorded. This threshold was defined based of minimization of the associated error. The use of High-Pass filters, such as Butterworth, have already been applied in other areas with similar purposes, such as baseline wander correction [53, 54].

3.3.3 Signal Segmentation

The signal segmentation was achieved using the gyroscope signal data. The raw gyroscope signal has a normalized baseline, which makes it useful for signal segmentation since it is possible to apply a segmentation threshold to the signal very easily. Additionally, the accelerometer or magnetometer signals would need the application of signal filters and baseline normalization methods to be dataset-proof, which would be redundant.

In this algorithm, the threshold was established at 0,8 rad/s, following several segmentation tests. Above the threshold, the smartwatch was considered in movement and the sensor data was recorded and stored.

This type of segmentation method causes the algorithm to perform a segmentation that results in two segments per eating movement: the table-to-mouth segment and the mouth-to-table segment. This leads to a total of 40 movements segmented, from which 10 were eating movements (table-to-mouth segments) and 30 not-eating movements (20 badly performed eating movements, as explained in section 3.3.1, plus 10 mouth-to-table movements).

3.3.3.1 Quantitative Metrics

There were several metrics that were calculated by the segmentation algorithm. Those were:

- Total time active
- Total time inactive
- Number of eating movements

3.3.4 Feature Generation

From the segmented signal, several features were generated for each signal component and each sensor. A set of 17 metrics was calculated for 27 signal components from the 3 sensors (accelerometer, gyroscope and magnetometer), which makes a total of 459 generated features. The whole set of generated features is displayed in Appendix B, divided by signal component, sensor and calculated metric.

These extracted features were then stored in an Attribute-Relation File Format (ARFF) file since they were to be analyzed using the software RapidMiner, which is able to read this type of files. This type of files is very simple and easily produced, which is an advantage since the step that writes the features into ARFF-files had to be introduced into the algorithm.

The ARFF-files are divided in two parts: the header and the data. The header part contains a list of the features (which are called "attributes") and what type of variable they are, and it also

contains the labels (which are called "classes") that exist. In this case, the labels are "Eating" and "Not-Eating". The data part contains the feature values, separated by commas, in the same order as the list in the header, followed by the label that those features correspond to.
This ARFF-file was then loaded into RapidMiner. RapidMiner is a software platform developed by the company of the same name that provides an integrated environment for machine learning and data mining. It is used for business and industrial applications as well as for research, education, training, rapid prototyping and application development and it supports all steps of the data mining process including result visualization, validation and optimization [55].

3.3.5 Feature Selection

Using RapidMiner, the extracted features were processed using Sequential Forward Selection. This step allowed for a reduction of the used features, which decreased feature redundancy and over-fitting risk, as previously explained.

3.3.6 Classification

The resulting features from the previous step were then used to create a predictive model based on four different machine learning algorithms: Decision Tree, k-NN, Naive Bayes and SVM.
To create and test the model, the feature data was distributed using cross-validation. Cross-validation is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. In a prediction problem, a model is usually given a dataset of known data, on which training is run (training dataset), and a dataset of unknown data, against which the model is tested (testing dataset). One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on the training set, and validating the analysis on the testing set. To reduce variability, multiple rounds of cross-validation are performed using different partitions, and the validation results are averaged over the rounds. Cross-validation is considered a reliable technique for algorithm evaluation [43].

3.3.7 Evaluation

Since this process of classification is binary, which means it only has two labels which are Positive and Negative, there are several performance metrics that can be computed. In this case, the Positive label was the label "Eating" while the Negative label was the label "Not-Eating".
The metrics that were computed were the following:

- Sensitivity
- Specificity
- Precision

- Accuracy
- ROC-curve
- Area Under Curve

3.4 Results and Discussion

3.4.1 Sitting and Standing

In Figure 3.8 the results of the low-pass weighted moving-average filter are shown in comparison with the raw accelerometer data.

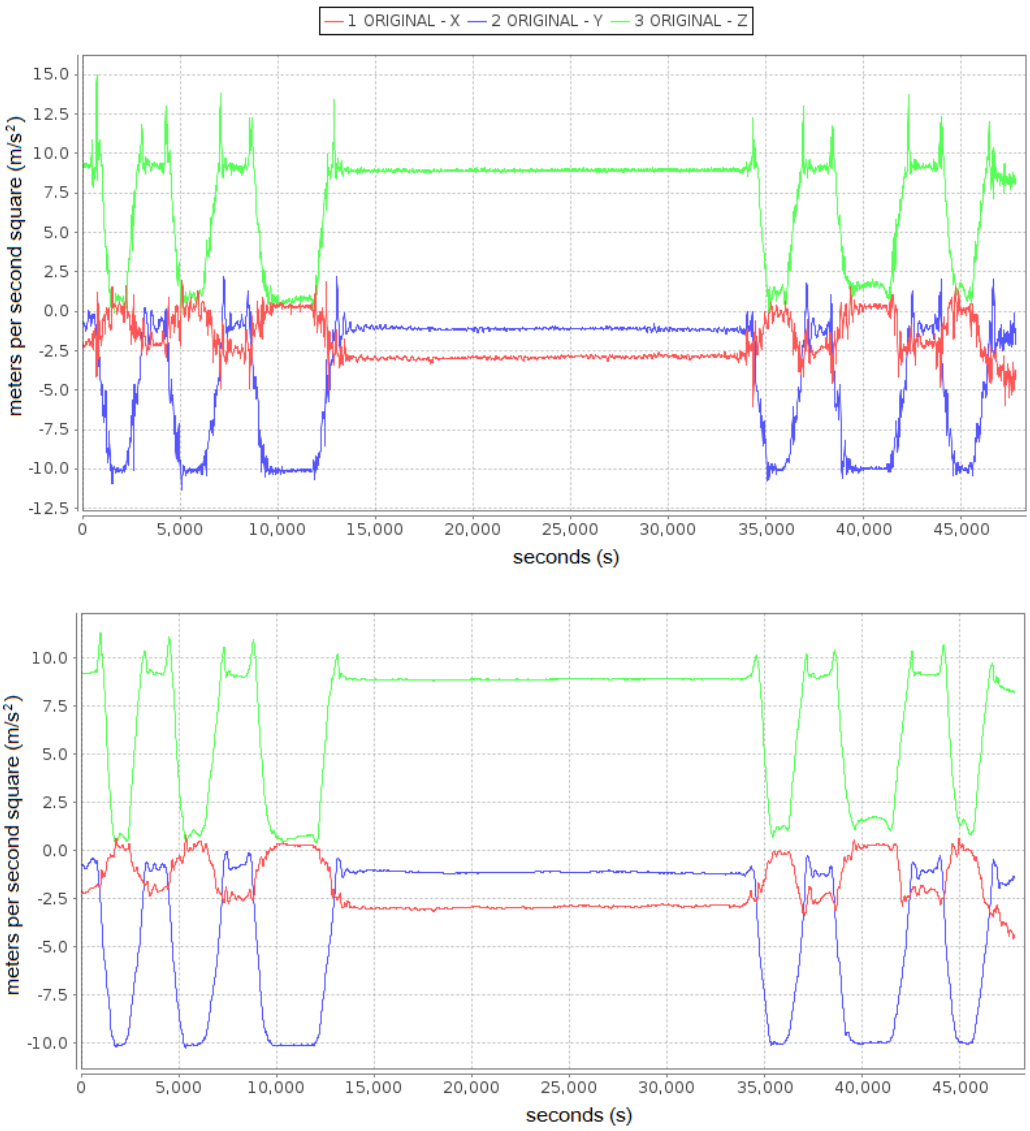

Figure 3.8: Results of the application of the low-pass weighted moving-average filter - the raw accelerometer data (top) and filtered accelerometer data (bottom)

It is possible to conclude that the initial noise captured by the accelerometer was removed and the signal became smoother without losing its stability and creating false results. This enables for a better signal processing and more correct results in the following steps.
In Figures 3.9 and 3.10 there is a comparison between several phone and screen positions while performing the same series of sitting and standing movements. It is possible to see what was previously explained, which is that the absolute value of the Y-axis of the accelerometer data was the correct signal component for the sitting and standing movement detection.

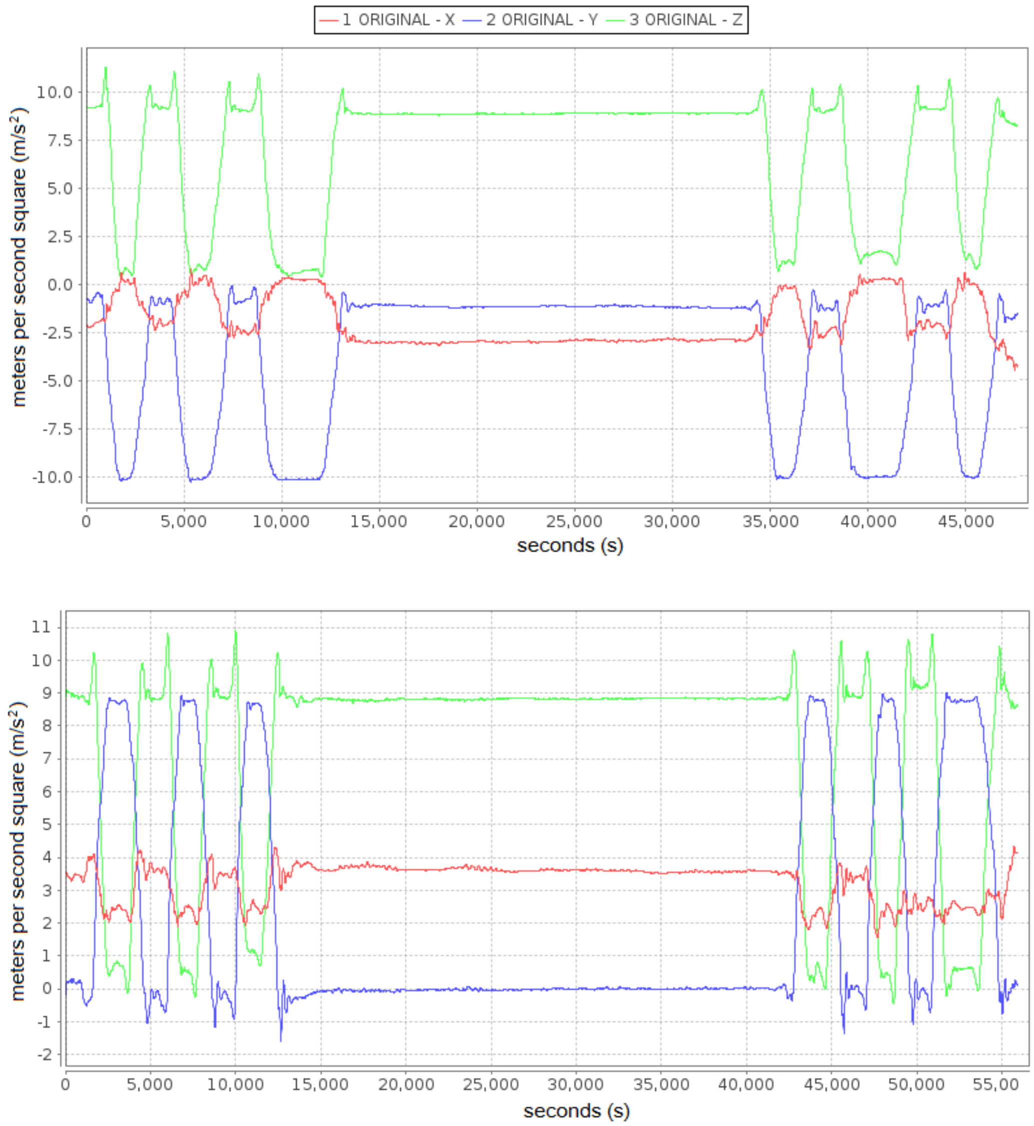

Figure 3.9: Comparison between data from smartphone in several phone positions with screen up - phone up (top) and phone down (bottom)

On the other hand, by comparing between several examples of the dataset, it was possible to estimate the movement detection thresholds. In Figure 3.11 this comparison is shown, as well as the location of the thresholds.

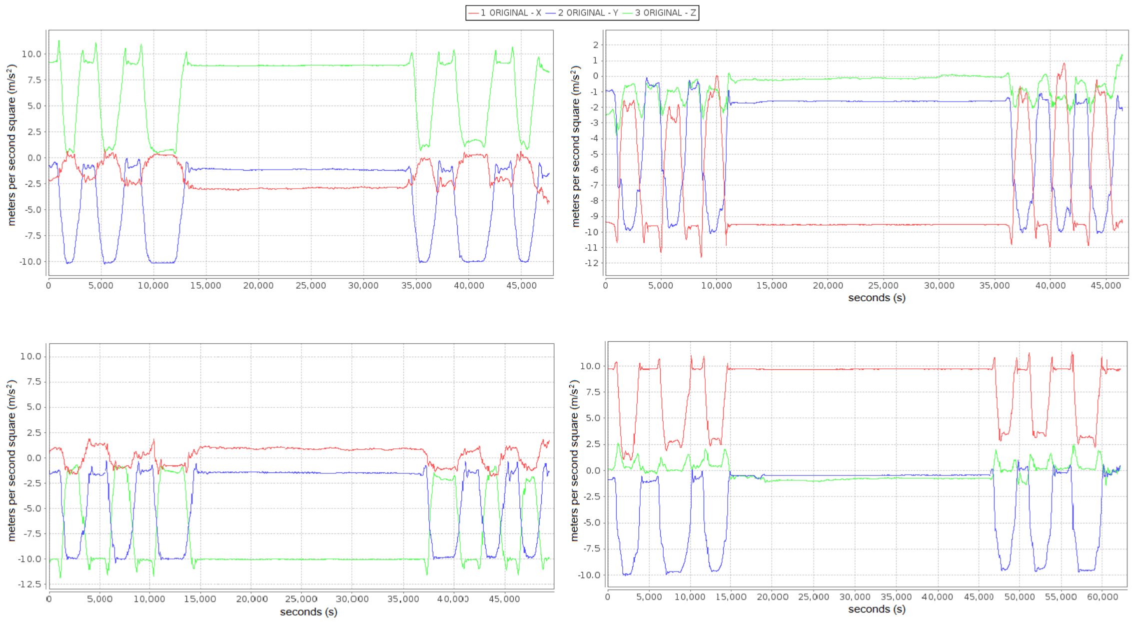

Figure 3.10: Comparison between data from smartphone in several screen positions with phone up - screen up (top left), screen down (bottom left), screen right (top right) and screen left (bottom right)

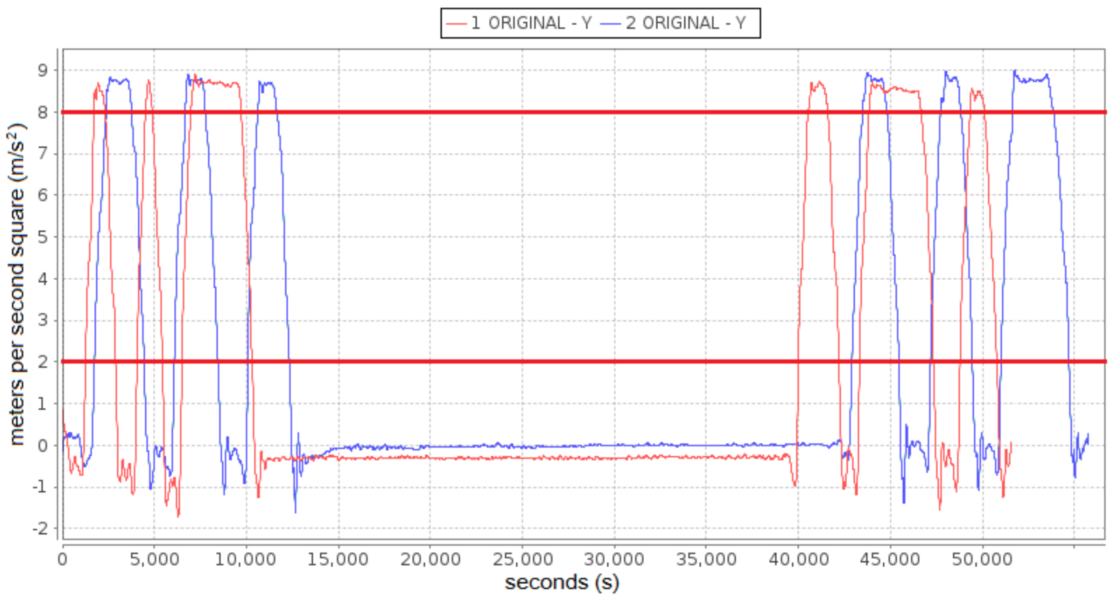

Figure 3.11: Example of threshold application for sitting and standing movement detection for two dataset individuals

Lastly, several metrics were computed, as was previously mentioned, which are shown in Figure 3.12. These metrics were evaluated in terms of error in order to understand the algorithm performance. The algorithm evaluation is displayed in Table 3.3.

```
Total time standing: 8.46 seconds
Total time sitting: 35.81 seconds
Number of sit/stand transitions: 12
```

Figure 3.12: Example of quantitative metrics for the sitting and standing movement in the IDE console

Table 3.3: Evaluation of the sitting and standing algorithm

Quantitative Metric	Mean Relative Error	Mean Absolute Error
Total time standing	13,34%	1,16 s
Total time sitting	4,41%	1,96 s
Number of transitions	2,78%	0,33

3.4.2 Eating

In Figure 3.13 it is possible to observe the results from the baseline normalization in comparison with the raw accelerometer data.

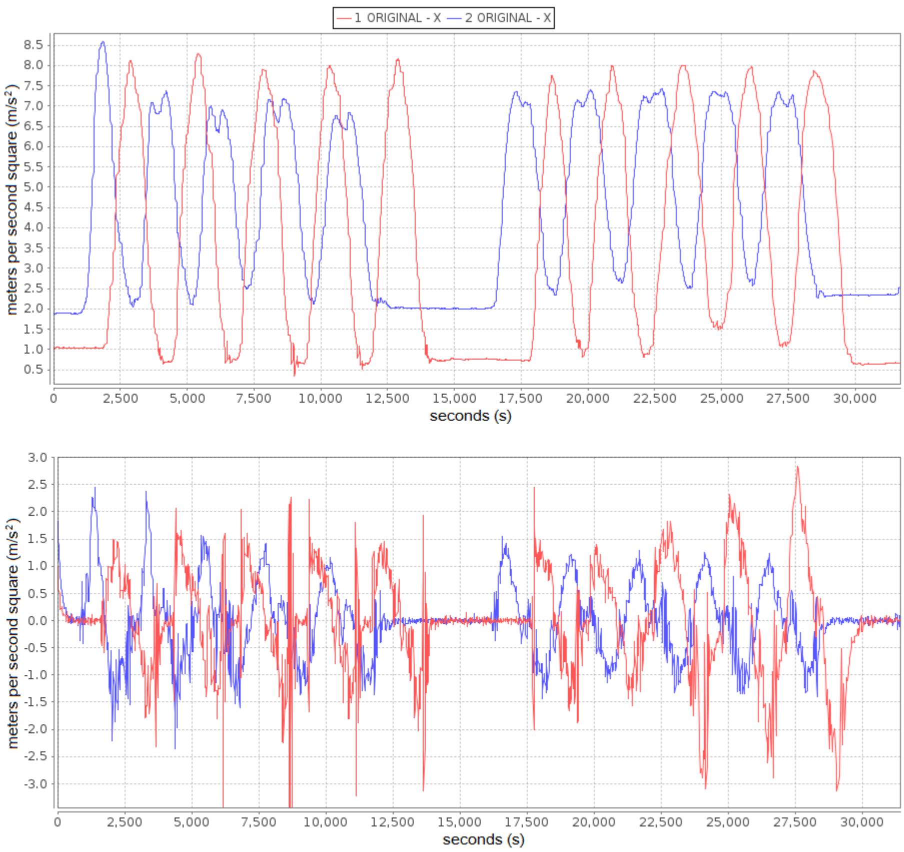

Figure 3.13: Results of the application of the Butterworth high-pass filter - the raw accelerometer data for two dataset individuals (top) and filtered accelerometer data for those individuals (bottom)

It is possible to conclude that the baseline was successfully normalized which resulted in the

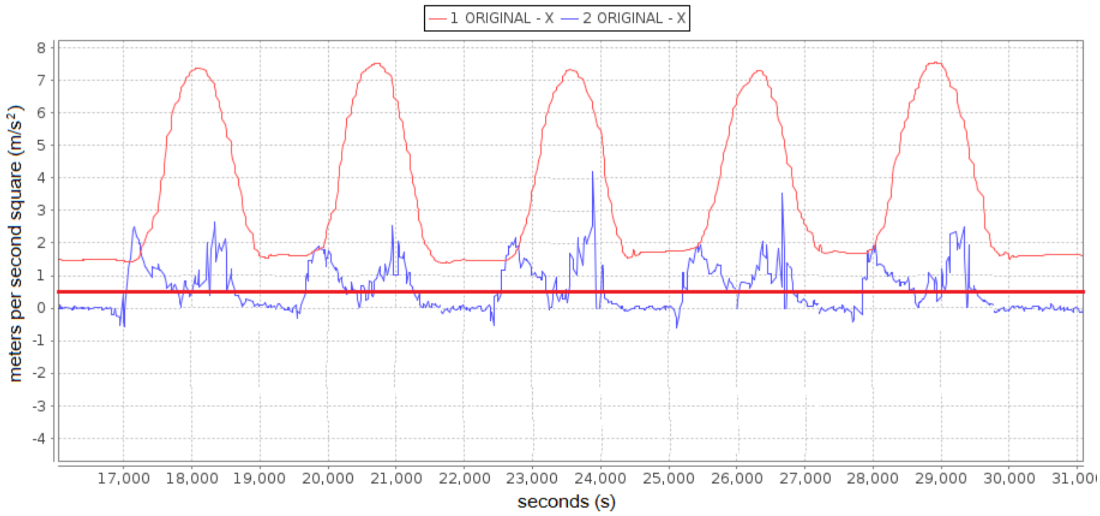

Figure 3.14: Example of threshold application for general activity detection - the X-axis raw accelerometer data (red) and the X-axis filtered accelerometer data (blue)

possibility of correctly applying a movement detection threshold, which was defined at $0{,}5 m/s^2$. If the absolute value of the filtered accelerometer signal was above this threshold, the upper limb was considered in movement. The application of the threshold is shown in Figure 3.14 with an example of a performed activity. The evaluation of this step is shown in Table 3.4.

In Figure 3.15 there is depicted the gyroscope signal and accelerometer signal during a series of eating movements. The applied threshold is shown to accurately segment the signal.

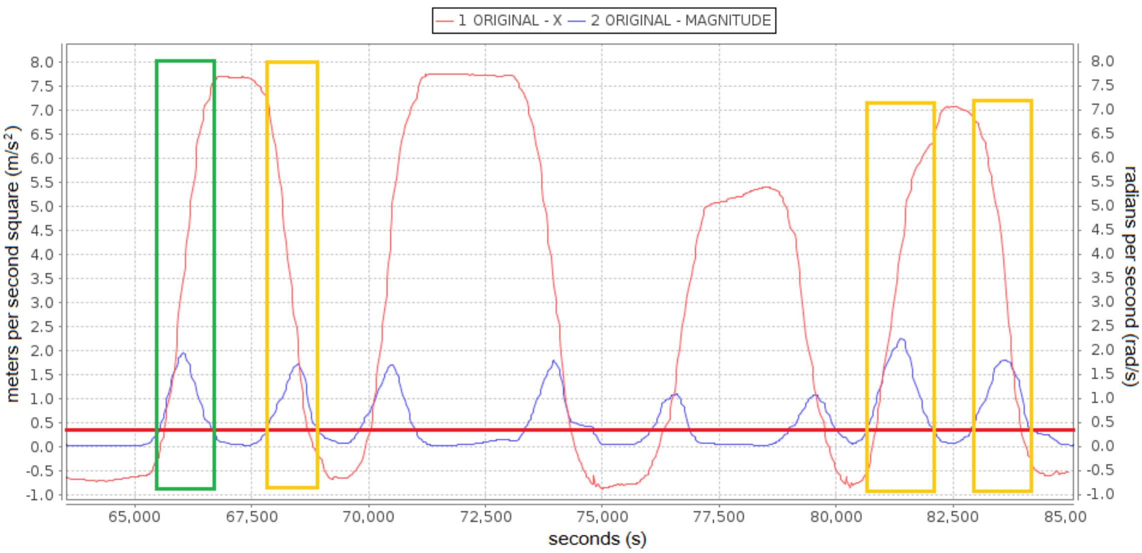

Figure 3.15: Result of the signal segmentation step for the accelerometer data (red) using the gyroscope data (blue) - applied threshold (red), eating movement (green) and not-eating movement (yellow)

This enabled for the features to be generated only for the eating and not-eating movements, avoiding moments where the user was idle. A correct signal segmentation is crucial for the algorithm's performance since the generated features have to match the specific movement. It is by using these features that the learning model will be trained and tested.

In Figure 3.16 there is an example of the result for the quantitative metrics computed by the algorithm. The evaluation in terms of the quantitative metrics is shown in Table 3.4, similarly as was made for the sittind and standing movements.

```
Total time active: 35.87 seconds
Total time inactive: 27.76 seconds
Total duration: 63.63 seconds
You performed 40 full movements
```

Figure 3.16: Example of quantitative metrics for the eating movement in the IDE console

Table 3.4: Evaluation of the eating algorithm - quantitative metrics

Quantitative Metric	Mean Relative Error	Mean Absolute Error
Total time active	6,33%	1,93 s
Total time inactive	9,86%	2,32 s
Number of eating movements	2,05%	0,82

Afterwards, using RapidMiner, the features undergone a feature selection step using Sequential Forward Selection. The selected features were then used to create 4 different learning models using 4 different classification algorithms, as previously explained. The performance of each of these algorithms was evaluated via 10-fold cross-validation and the results are shown in Table 3.5, as well as the selected features. In Appendix C the confusion matrices and ROC-curves are displayed. Overall, the performance of the classification algorithms increased by 4% when feature selection was used comparing to when it was not used.

Table 3.5: Evaluation of the eating algorithm - algorithm's performance

Classifier	Accuracy	Precision	Sensitivity	AUC	Features used
Decision Tree	92,99%	92,67%	98,93%	0,871	Pitch_median, RawMagX_entropy, RawMagX_maxAVG, Yaw_kurtosis, Roll_rms
k-NN	94,99%	94,93%	98,94%	0,933	Roll_maxAVG, Pitch_median, Roll_peakHeight, Yaw_max, Yaw_peakHeight
Naive Bayes	91,93%	92,42%	97,62%	0,845	RawGyroX_peakHeight, RawMagY_min, Pitch_median, SfMagY_skewness, RawMagY_maxAVG
SVM	89,82%	91,63%	95,94%	0,834	Pitch_median, RawMagY_max Roll_max, Yaw_min RawMagX_peakHeight

The performances of the several classification algorithms were, overall, very similar to one another. However, the Decision Tree classifier was chosen since it offers a superior stability between precision, speed and interpretability of the results [56]. Besides this, the Decision Tree algorithm in one of the most commonly used classifers in human activity recognition [41]. Generally, this algorithm is computationally less expensive than more complex classifiers, which is a key feature since the developed algorithm needs to efficiently run in real-time and during the daily activity of the user without over-spending the devices' battery.
In Figure 3.17 the resulting Decision Tree algorithm computed by RapidMiner using the selected features is displayed.

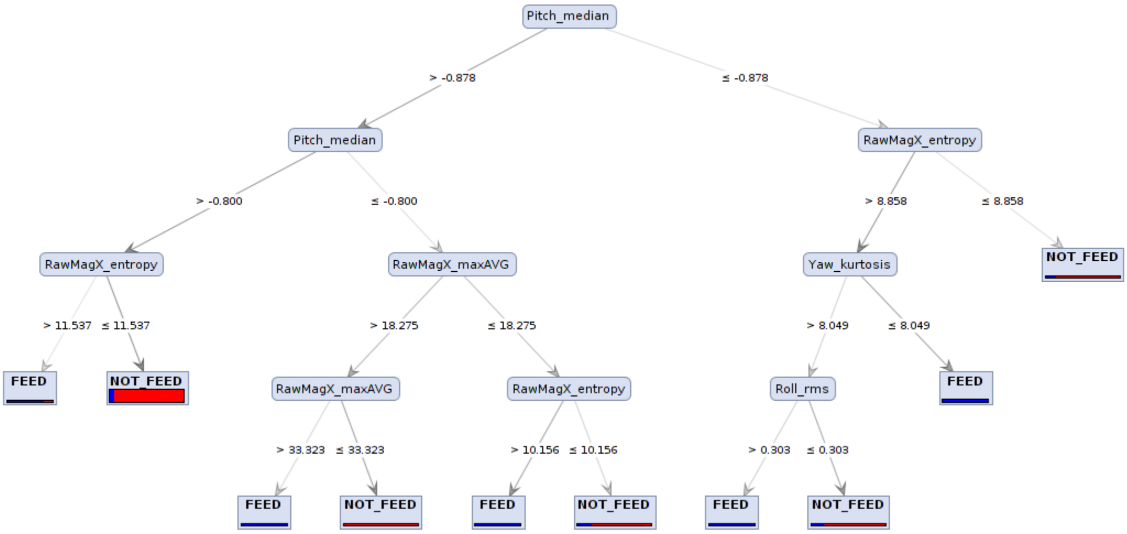

Figure 3.17: Resulting Decision Tree algorithm in RapidMiner

The purpose of this Decision Tree is to be applied in the final phase of this dissertation, which is the development of an exergame to detect the eating movement.

Chapter 4

Exergame

This chapter describes the development of an exergame that is intended to be used in stroke rehabilitation, namely at home and in stroke rehabilitation centers. Firstly there is a brief introduction where the game interface is fully explained, regarding buttons and objects, as well as game objectives. Afterwards, the game logic is extensively described. To conclude, the final results are analyzed and discussed in terms of impact in stroke rehabilitation.

4.1 Introduction

This exergame serves as a proof of concept of a rehabilitation application that uses the developed algorithm. This game is a part of "ExerGames", a full gaming solution for Rehabilitation and Fall Prevention developed at FhP-AICOS. This game is named "Go Fish" and it aims at ADL stroke rehabilitation with a specific focus on the upper limb.
The game was developed in C# using Unity and its integrated IDE, MonoDevelop.

4.1.1 Objectives

The objective of the game is to collect good fish from the river using a fishing rod, while avoiding bad fish. Good fish exist in larger quantity as opposed to bad fish.
From a rehabilitation point of view, the exergame has two objectives: promote physical movement of the upper limb in order to restore the eating capability and, on the other hand, offer some cognitive challenge to the player, in this case via the different fish colours.

4.1.2 Interface

The interface of the game is purposely simple, since the requirements focus on age and literacy independency. This means that this type of games should be playable by anyone and should therefore be easily understandable.
In Figure 4.1 there is an example of the game interface and its different components. Each game

component is marked and described below. The objects which are not marked are merely decorative and have no impact on the game.

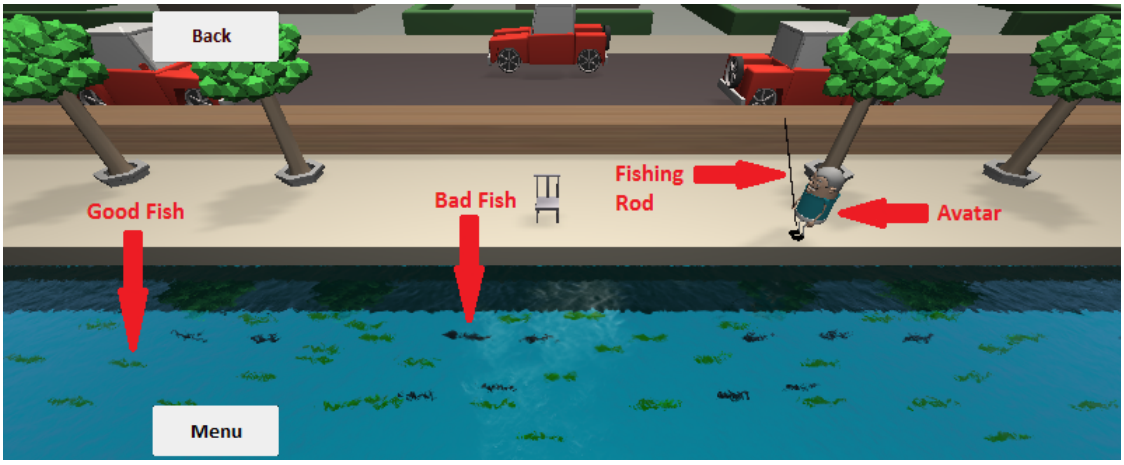

Figure 4.1: Example of the "Go Fish" interface

4.1.3 System Architecture for the Exergame

In Figure 4.2 there is a general diagram depicting the full architecture of the exergame.
In this chapter, the full process of movement detection is made online via Bluetooth. For this part, the aim is to apply the developed movement classification methods over the incoming sensor data to obtain movement information relative to the execution of the target movements. When the player executes a sitting/standing sequence or an eating sequence, the developed movement classification methods produce a useful logical information that is treated as a player event. This information is used in the game logic for progressing in the game and obtaining success or failure information.

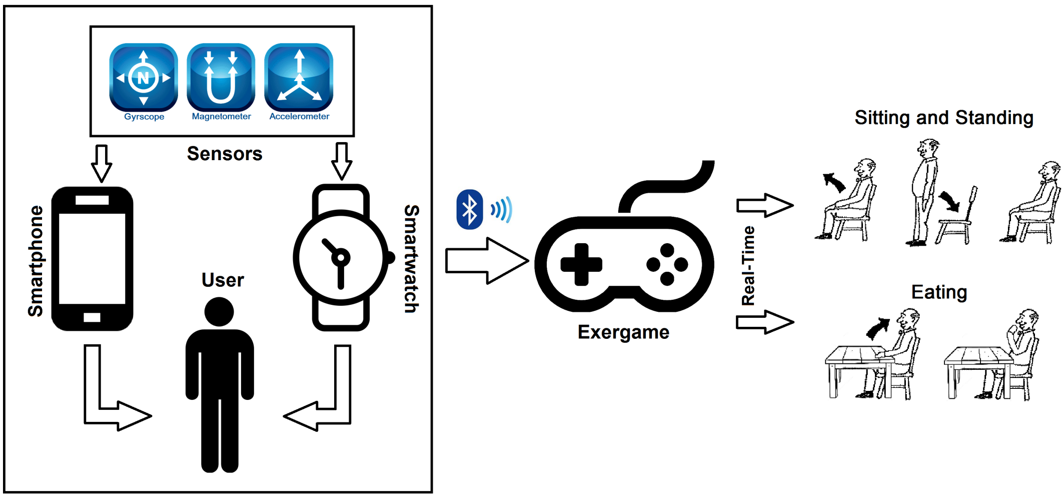

Figure 4.2: Diagram depicting the game architecture

The three inertial sensors explained before are already integrated on both mobile devices and these are worn by the user according to the instructions mentioned previously.
The dataset is collected in real-time with the movement-detection algorithm via a Bluetooth connection already implemented by FhP-AICOS. This connection is made in its "Smartfeet" application, which serves as a controller for the "ExerGames" gaming solution. This application is run in both the smartwatch and the smartphone.
The sensory data is then used to feed the movement analysis algorithm, which was explained in the previous section. This algorithm was re-writen in C# and is divided in two parts: the sitting/standing detection, using the threshold-based approach, and the eating detection, based on the Decision Tree algorithm.

4.2 Exergame Development

4.2.1 Game Algorithm

The algorithm for the exergame is described in Figure 4.3 as a fluxogram.

The sensory data is collected via a Bluetooth connection, which sends the data from all the three sensors from the mobile devices to the exergame. Afterwards, if the data comes from the smartphone, the thresholds that were previously defined are applied to the accelerometer signal, which results in a classification of which state the user is in: sitting, standing or in transition. This inspection is continuous untill the accelerometer data crosses another threshold and the state changes, for which the quantitative metrics mentioned previously are computed.
On the other hand, if the data comes from the smartwatch, the threshold for the gyroscope signal is applied which leads to a segmentation of the signal. If the signal remains above the threshold, the sensor data is stored as a segment untill the gyroscope signal crosses the threshold. When this happens, the segmentation finishes and the segments are sent to the classifier, which results in a classification output: eating or not-eating.
The output of this algorithm will then be used by the game logic to produce different events in the game, such as avatar animations and score.

4.2.2 Game Logic

The game logic for the exergame is described in Figures 4.4 and 4.5 as a fluxogram.

The game starts with the avatar automatically moving from its starting position on the right of the chair to the front of the chair and then turning to face the screen. From this point, the game is awaiting sensory data for the avatar to move any further.
For the game to proceed, the user has to perform a sitting movement, which leads the avatar to sit on the chair. This movement activates the start of the actual game. In the river, the fish start randomly jumping to the outside and going back in. The fish may be yellow - good fish - or red - bad fish.
While a good fish is in the air, the user has to perform an eating movement to activate the fishing

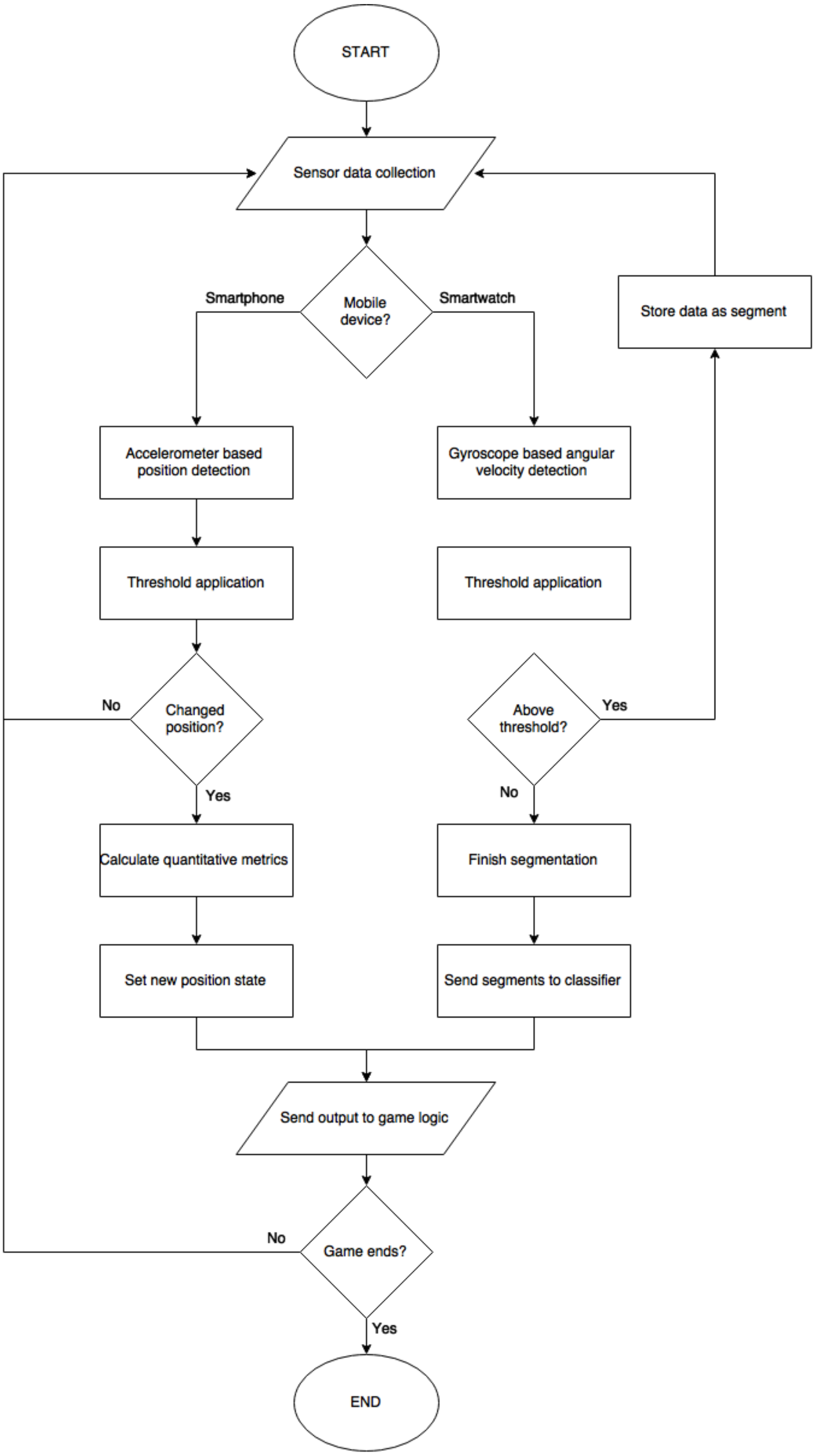

Figure 4.3: Fluxogram depicting the user activity algorithm

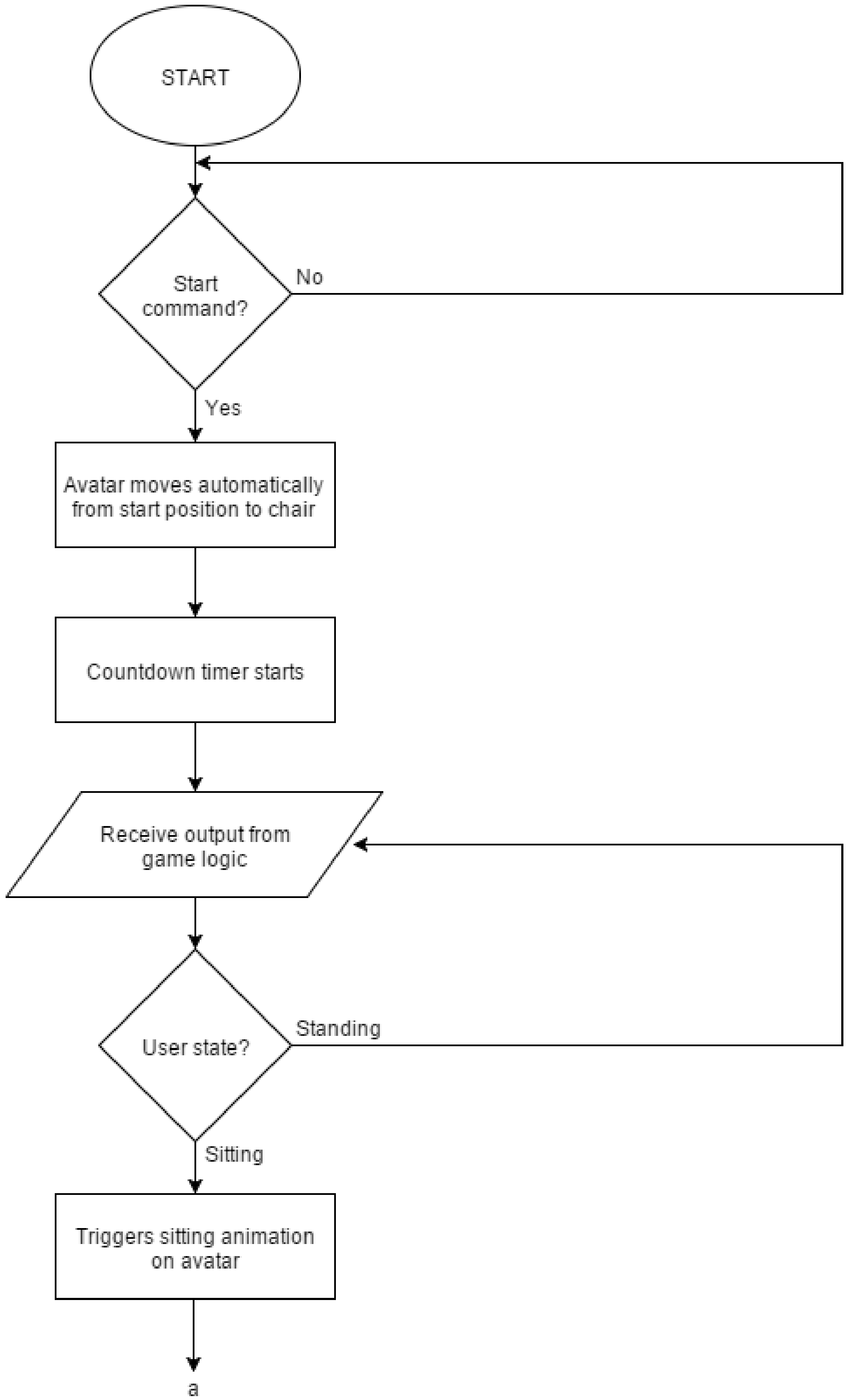

Figure 4.4: Fluxogram depicting the game logic - Part 1

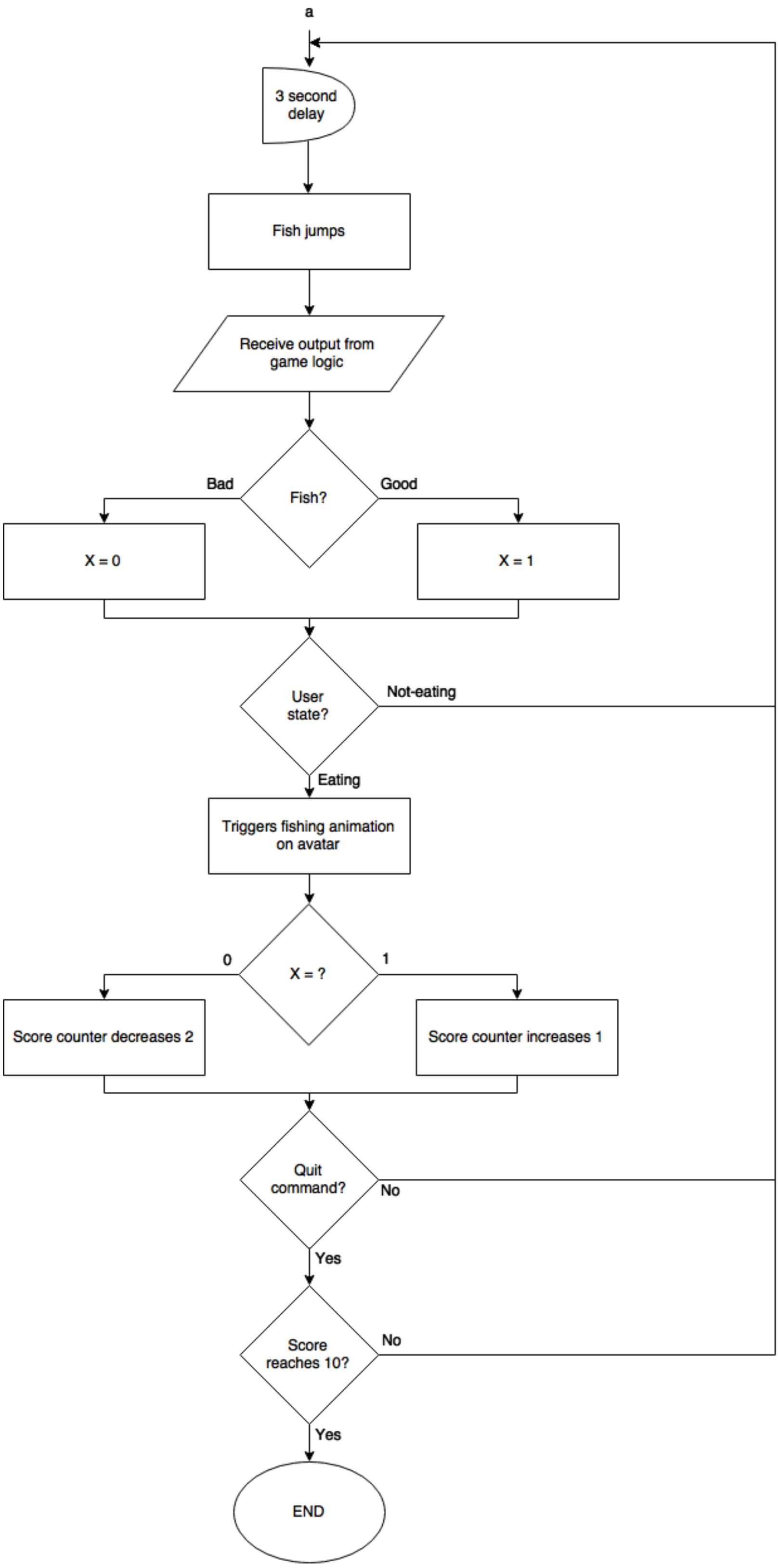

Figure 4.5: Fluxogram depicting the game logic - Part 2

rod and pull the fish to him. This increments the fish counter by 1. However, if the fish that is jumping is red, that means the user has to remain still and not catch it. By catching bad fish, the counter decreases by 2.
The game ends in one of two different ways: either the 60 second countdown timer finishes or the user reaches a score of 10.

4.2.3 Game Score

At the end of the game, the player is shown a screen with an overview of his performance. This screen shows the total number of fish caught and the time it took to catch them. It can also show other quantitave metrics that could be useful for the stroke therapist, such as the total number of eating movements and the average duration of an eating movement. These metrics correspond to the ones calculated during the prototype development phase.
In addition to this, the score screen also displays an evaluation in terms of the ICF scale. As previously mentioned, there are several indexes that aim at evaluating a stroke patient's independence and general status after stroke. It is particularly useful for a stroke therapist to apply these indexes to the patients that are being treated, since that way it is possible to know quantitatively how a patient is at each moment. This has several advantages; on one hand, it helps the stroke therapist in choosing a specific treatment to follow. Additionally, it also, for instance, makes the communication between therapists easier. Therefore, it is possible to conclude that it would be extremely useful if the developed exergame could instantly assess the patient based on his game performance and assign a value on a specific stroke scale.
Stroke scales, however, are sometimes very limited for the evaluation of some activities. For instance, the eating activity, although mentioned in the Barthel Index, refers to the process of cutting food or spreading butter and not specifically to the movement of eating. In the European Stroke Scale, the eating movement is not even specifically mentioned, but instead there are listed two general types of arm movement. This leads to a necessity of using a more detailed scale.

xxx.0	NO impairment	(none, absent, negligible,…)	0-4 %
xxx.1	MILD impairment	(slight, low,…)	5-24 %
xxx.2	MODERATE impairment	(medium, fair,...)	25-49 %
xxx.3	SEVERE impairment	(high, extreme, …)	50-95 %
xxx.4	COMPLETE impairment	(total,…)	96-100 %
xxx.8	not specified		
xxx.9	not applicable		

Figure 4.6: Evaluation scale of the ICF [6] - *xxx* represents the disability code, in this case d550

In this case, the International Classification of Functioning, Disabilities and Health (ICF) was used. The ICF has a very broad spectrum of disabilities and a very thorough evaluation scale. For example, in ICF a clear distinction between eating and preparing meals is made, where both fall in the chapter "Activities and Participation", but the first one is considered in section "Self Care"

whilst the second is in section "Domestic Life". In the ICF, the eating activity has the code d550, which is followed by an evaluation from 0 to 4 [6]. The evaluation scale is shown in Figure 4.6. Based on this evaluation scale, the exergame then performs a calculation based on the player's performance in order to assign a value in the ICF. This calculation takes into consideration two factors: the number of fish caught and the time it took to catch them.
Firstly, the game calculates a basic proportion of the final score in percentage. Afterwards, based on the fact that an healthy person takes, on average, 4 seconds to catch a fish and wait for the next one to jump, the game calculates how much time that person would have taken to catch the number of fish caught by the player. The 4 second interval results from the sum of 3 seconds, the programmed time between fish jumping, and 1 second, the average time to catch a fish. The game then calculates a basic proportion of the time in percentage. With these two values, the game calculates the mean value and subtracts it to the total of 100%, thus giving the final score in percentage for the ICF.

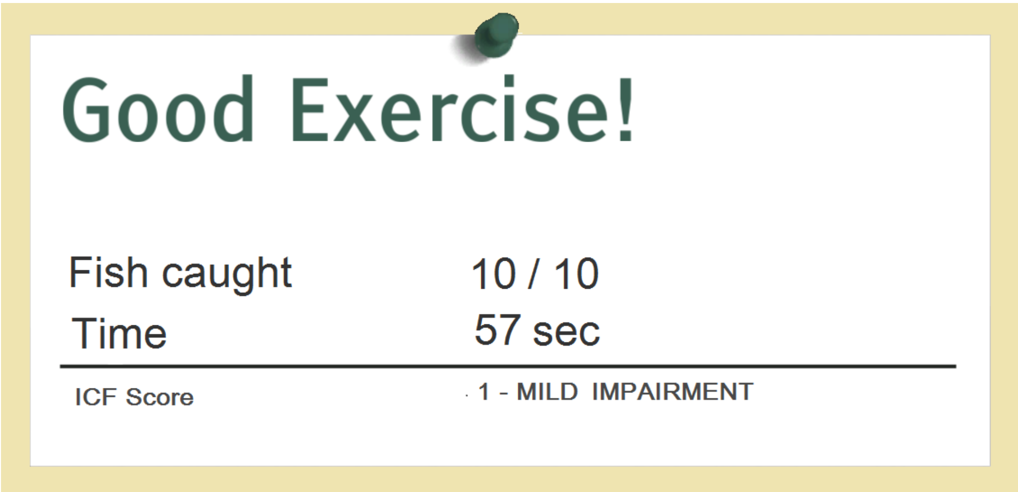

Figure 4.7: Example of the "Go Fish" score screen

Below, there is an example of a game performance. For instance:

1. I finish the game with a score of 10 in 10
2. $10/10$, in percentage, equals 100%
3. But, it took me 57 seconds to reach the score 10
4. And usually it should take $4 * 10$ which is 40 seconds
5. $40/57$, in percentage, equals 70,18%
6. The mean value between score and time is (100%+70,18%)/2, which equals 85,09%
7. The final score is $100\% - 85,09\%$, which equals 14,91%
8. This score corresponds to a score of 1-MILD IMPAIRMENT in the ICF

Following the previous example, in Figure 4.7 there is an example of the final score screen, when the game ends. This screen is displayed for the patient, which means it does not have all the quantitative metrics mentioned previously since those would only be useful for the stroke therapist.

Chapter 5

Conclusions

5.1 Achievements

The primary objective of this project regarding the analysis of mobile device sensory data and classification of ADLs for post-stroke patients was achieved using two approaches: a threshold-based approach, for the sitting and standing activities, and a machine learning approach, for the eating activity.

The threshold-based approach used a collected dataset of 26 individuals and achieved a mean relative error of 6,84% using only accelerometer data. This approach also computed the total time standing, total time sitting and the total number of transitions sit/stand and stand/sit.

The machine learning approach relied on the same collected dataset of 26 individuals. Several classification algorithms were tested and ultimately a Decision Tree algorithm was chosen since it had a good performance, offered a superior stability between precision, speed and interpretability of the results and was computationally inexpensive. This algorithm achieved an accuracy of 92,99% and a classification error of only 7,01%. The eating movement is a severely impaired activity resulting of stroke and it is still lacking research when in comparison with other ADLs.

The secondary objective, which was designing an exergame using the previously developed classification algorithm, was also achieved. This exergame promoted physical activity by the stroke patient and it also contextualized the patient's in-game performance in terms of the ICF scale, which is an advantage for the stroke therapist.

5.2 Future Work

This project is only a prototype, which means that some possible improvements were identified during its development phase. Those are:

- Use a machine learning approach for the classification of the sitting and standing activities
- Explore frequency-domain features for the feature generation phase, using, for example, wavelet transforms and FFT

- Develop an Android application for the physiotherapist and patient to function in addition to the exergame
- Collect datasets in unsupervised environments, preferably in a domestic environment and with people who suffered a stroke
- Use only the smartwatch for the detection of both activities (this would require an initial calibration phase)
- Explore other stroke-related impaired activities to detect with the smartwatch
- Explore approaches that reduce the number of False Positives (this would allow for a true application of this project)
- Test the exergame with stroke patients

References

[1] R. D. Adams, M. Victor *et al.*, *Adams and Victor's principles of neurology*. McGraw-Hill Medical Pub. Division New York, 2005, vol. 179.

[2] P. Langhorne, F. Coupar, and A. Pollock, "Motor recovery after stroke: a systematic review," *The Lancet Neurology*, vol. 8, no. 8, pp. 741–754, 2009.

[3] C. L. Taylor, *The biomechanics of control in upper-extremity prostheses*. National Academy of Sciences, 1955.

[4] A. K. Jain, R. P. Duin, and J. Mao, "Statistical pattern recognition: A review," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 22, no. 1, pp. 4–37, 2000.

[5] A. M. Mendonça, "Computer aided diagnosis: Evaluation," *Master in Bioengineering*, 2014.

[6] W. H. Organization, *International Classification of Functioning, Disability and Health: ICF*. World Health Organization, 2001.

[7] K. Aho, P. Harmsen, S. Hatano, J. Marquardsen, V. Smirnov, and T. Strasser, "Cerebrovascular disease in the community: results of a who collaborative study," *Bulletin of the World Health Organization*, vol. 58, no. 1, p. 113, 1980.

[8] R. L. Sacco, S. E. Kasner, J. P. Broderick, L. R. Caplan, A. Culebras, M. S. Elkind, M. G. George, A. D. Hamdan, R. T. Higashida, B. L. Hoh *et al.*, "An updated definition of stroke for the 21st century a statement for healthcare professionals from the american heart association/american stroke association," *Stroke*, vol. 44, no. 7, pp. 2064–2089, 2013.

[9] A. Shuaib and V. C. Hachinski, "Mechanisms and management of stroke in the elderly." *CMAJ: Canadian Medical Association Journal*, vol. 145, no. 5, p. 433, 1991.

[10] L. B. Goldstein and D. L. Simel, "Is this patient having a stroke?" *Jama*, vol. 293, no. 19, pp. 2391–2402, 2005.

[11] S. S. Rathore, A. R. Hinn, L. S. Cooper, H. A. Tyroler, and W. D. Rosamond, "Characterization of incident stroke signs and symptoms findings from the atherosclerosis risk in communities study," *Stroke*, vol. 33, no. 11, pp. 2718–2721, 2002.

[12] T. A. Schweizer and R. L. Macdonald, *The Behavioral Consequences of Stroke*. Springer, 2014.

[13] T. A. I. R. I. Stroke, "Recommendations for clinical trial evaluation of acute stroke therapies." *Stroke; a journal of cerebral circulation*, vol. 32, no. 7, p. 1598, 2001.

[14] W. S. Organization, "Stroke: Annual report," 2013.

[15] D. G. da Saúde, "Portugal: Doenças cérebro-cardiovasculares em números," 2013.

[16] P. W. Duncan, R. Zorowitz, B. Bates, J. Y. Choi, J. J. Glasberg, G. D. Graham, R. C. Katz, K. Lamberty, and D. Reker, "Management of adult stroke rehabilitation care a clinical practice guideline," *Stroke*, vol. 36, no. 9, pp. e100–e143, 2005.

[17] L. Smith *et al.*, *Management of Patients With Stroke: Rehabilitation, Prevention and Management of Complications, and Discharge Planning: a National Clinical Guideline*. Scottish Intercollegiate Guidelines Network, 2010, vol. 118.

[18] P. Lindsay, M. Bayley, C. Hellings, M. Hill, E. Woodbury, S. Phillips *et al.*, "Canadian best practice recommendations for stroke care (updated 2008)," *Canadian Medical Association Journal*, vol. 179, no. 12, pp. S1–S25, 2008.

[19] N. Choices, "National stroke strategy," 2011.

[20] C. Collin, D. Wade, S. Davies, and V. Horne, "The barthel adl index: a reliability study," *Disability & Rehabilitation*, vol. 10, no. 2, pp. 61–63, 1988.

[21] L. Hantson, W. De Weerdt, J. De Keyser, H. Diener, C. Franke, R. Palm, M. Van Orshoven, H. Schoonderwalt, N. De Klippel, and L. Herroelen, "The european stroke scale." *Stroke*, vol. 25, no. 11, pp. 2215–2219, 1994.

[22] E. Taub and D. M. Morris, "Constraint-induced movement therapy to enhance recovery after stroke," *Current atherosclerosis reports*, vol. 3, no. 4, pp. 279–286, 2001.

[23] A. Siebers, U. Öberg, and E. Skargren, "The effect of modified constraint-induced movement therapy on spasticity and motor function of the affected arm in patients with chronic stroke," *Physiotherapy Canada*, vol. 62, no. 4, pp. 388–396, 2010.

[24] S. J. Page, P. Levine, S. A. Sisto, and M. V. Johnston, "Mental practice combined with physical practice for upper-limb motor deficit in subacute stroke," *Physical Therapy*, vol. 81, no. 8, pp. 1455–1462, 2001.

[25] J. A. Brown, "Recovery of motor function after stroke," *Progress in brain research*, vol. 157, pp. 223–228, 2006.

[26] J. V. Graham, C. Eustace, K. Brock, E. Swain, and S. Irwin-Carruthers, "The bobath concept in contemporary clinical practice," *Topics in stroke rehabilitation*, vol. 16, no. 1, pp. 57–68, 2009.

[27] K. R. Lohse, C. G. Hilderman, K. L. Cheung, S. Tatla, and H. M. Van der Loos, "Virtual reality therapy for adults post-stroke: a systematic review and meta-analysis exploring virtual environments and commercial games in therapy," *PloS one*, vol. 9, no. 3, p. e93318, 2014.

[28] J. E. Gallichio, "Pharmacologic management of spasticity following stroke," *Physical therapy*, vol. 84, no. 10, pp. 973–981, 2004.

[29] S. B. O'Sullivan, T. J. Schmitz, and G. Fulk, *Physical rehabilitation*. FA Davis, 2013.

[30] C. L. VanPutte, J. Regan, A. Russo, R. R. Seeley, T. D. Stephens, and P. Tate, *Seeley's anatomy & physiology*. McGraw-Hill, 2014.

[31] M. N. Boulos, S. Wheeler, C. Tavares, and R. Jones, "How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from ecaalyx," *Biomedical engineering online*, vol. 10, no. 1, p. 24, 2011.

[32] A. G. Wilde, "Activity recognition for motion-aware pervasive systems," Ph.D. dissertation, University of Fribourg (Switzerland), 2011.

[33] J. K. Aggarwal and Q. Cai, "Human motion analysis: A review," *Computer vision and image understanding*, vol. 73, no. 3, pp. 428–440, 1999.

[34] S. Ayub, A. Bahraminisaab, and B. Honary, "A sensor fusion method for smart phone orientation estimation," 2012.

[35] A. Campilho, "Computer aided diagnosis: Classification," *Master in Bioengineering*, 2014.

[36] ——, "Computer aided diagnosis: Feature extraction," *Master in Bioengineering*, 2014.

[37] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "A public domain dataset for human activity recognition using smartphones," in *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN*, 2013.

[38] E. Sreejith, A. Verma, and A. Srividya, "Fault diagnosis of rolling element bearing using time-domain features and neural networks," in *Industrial and Information Systems, 2008. ICIIS 2008. IEEE Region 10 and the Third international Conference on*. IEEE, 2008, pp. 1–6.

[39] D. L. Vail, J. D. Lafferty, and M. M. Veloso, "Feature selection in conditional random fields for activity recognition," in *Intelligent Robots and Systems, 2007. IROS 2007. IEEE/RSJ International Conference on*. IEEE, 2007, pp. 3379–3384.

[40] J. Reunanen, "Overfitting in making comparisons between variable selection methods," *The Journal of Machine Learning Research*, vol. 3, pp. 1371–1382, 2003.

[41] A. G. Wilde, "An overview of human activity detection technologies for pervasive systems," in *Seminar paper. Pervasive and Artificial Intelligence Group of University of Southampton*, 2010.

[42] B. Aguiar, J. Silva *et al.*, "Monitoring physical activity and energy expenditure with smartphones," in *Biomedical and Health Informatics (BHI), 2014 IEEE-EMBS International Conference on*. IEEE, 2014, pp. 664–667.

[43] A. Anjum and M. U. Ilyas, "Activity recognition using smartphone sensors," in *Consumer Communications and Networking Conference (CCNC), 2013 IEEE*. IEEE, 2013, pp. 914–919.

[44] V. A. F. Bento, "Sword – an intelligent vibratory wearable device to improve rehabilitation in stroke patients," Ph.D. dissertation, University of Aveiro, 2012.

[45] A. M. Khan, Y.-K. Lee, S. Lee, and T.-S. Kim, "Human activity recognition via an accelerometer-enabled-smartphone using kernel discriminant analysis," in *Future Information Technology (FutureTech), 2010 5th International Conference on*. IEEE, 2010, pp. 1–6.

[46] L. Atallah, B. Lo, R. Ali, R. King, and G.-Z. Yang, "Real-time activity classification using ambient and wearable sensors," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 13, no. 6, pp. 1031–1039, 2009.

[47] Z. He and L. Jin, "Activity recognition from acceleration data based on discrete consine transform and svm," in *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on*. IEEE, 2009, pp. 5041–5044.

[48] T. Saponas, J. Lester, J. Froehlich, J. Fogarty, and J. Landay, "ilearn on the iphone: Real-time human activity classification on commodity mobile phones," *University of Washington CSE Tech Report UW-CSE-08-04-02*, vol. 2008, 2008.

[49] Y.-J. Hong, I.-J. Kim, S. C. Ahn, and H.-G. Kim, "Activity recognition using wearable sensors for elder care," in *Future Generation Communication and Networking, 2008. FGCN'08. Second International Conference on*, vol. 2. IEEE, 2008, pp. 302–305.

[50] J. He, H. Li, and J. Tan, "Real-time daily activity classification with wireless sensor networks using hidden markov model," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*. IEEE, 2007, pp. 3192–3195.

[51] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen, "Activity classification using realistic data from wearable sensors," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 10, no. 1, pp. 119–128, 2006.

[52] A. M. Khan, Y.-K. Lee, S. Y. Lee, and T.-S. Kim, "A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 14, no. 5, pp. 1166–1172, 2010.

[53] C. J. De Luca, L. D. Gilmore, M. Kuznetsov, and S. H. Roy, "Filtering the surface emg signal: Movement artifact and baseline noise contamination," *Journal of biomechanics*, vol. 43, no. 8, pp. 1573–1579, 2010.

[54] M. Blanco-Velasco, B. Weng, and K. E. Barner, "Ecg signal denoising and baseline wander correction based on the empirical mode decomposition," *Computers in biology and medicine*, vol. 38, no. 1, pp. 1–13, 2008.

[55] F. Jungermann, "Information extraction with rapidminer," in *Proceedings of the GSCL Symposium'Sprachtechnologie und eHumanities*. Citeseer, 2009, pp. 50–61.

[56] V. P. Bresfelean, "Analysis and predictions on students' behavior using decision trees in weka environment," in *Information Technology Interfaces, 2007. ITI 2007. 29th International Conference on*. IEEE, 2007, pp. 51–56.

[57] J. Newman, H. Zhou, and H. Hu, "Inertial sensors for motion detection of human upper limbs," *Sensor Review*, vol. 27, no. 2, pp. 151–158, 2007.

[58] G. Bieber, T. Kirste, and B. Urban, "Ambient interaction by smart watches," in *Proceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 2012, p. 39.

[59] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman, "Activity recognition from accelerometer data," in *AAAI*, vol. 5, 2005, pp. 1541–1546.

[60] P. Siirtola and J. Röning, "Recognizing human activities user-independently on smartphones based on accelerometer data," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 1, no. 5, 2012.

[61] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SigKDD Explorations Newsletter*, vol. 12, no. 2, pp. 74–82, 2011.

Appendix A

Demographic information of the dataset individuals

Table A.1: Information of the first dataset individuals

User	U1	U2	U3	U4	U5	U6	U7	U8	Mean±Std
Age	22	24	22	22	23	23	23	22	22,63±0,74
Gender	M	M	F	M	M	M	M	M	7M, 1F

Table A.2: Information of the second dataset individuals

User	U1	U2	U3	U4	U5	U6	Mean±Std
Age	69	68	76	64	71	69	69,50±3,94
Gender	F	M	M	F	F	F	2M, 4F

Table A.3: Information of the third dataset individuals

User	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	Mean±Std
Age	68	75	76	78	70	78	69	77	64	67	66	80	72,33±5,55
Gender	M	F	F	F	M	M	F	M	M	F	F	F	5M, 7F

Appendix B

Extracted features for the eating movement classification

Table B.1: Extracted features for the eating movement classification - Part 1

			Mean	**Median**	**Maximum**	**Minimum**	**Root Mean Square**
Accelerometer	Raw	X	RawAccX_mean	RawAccX_median	RawAccX_max	RawAccX_min	RawAccX_rms
		Y	RawAccY_mean	RawAccY_median	RawAccY_max	RawAccY_min	RawAccY_rms
		Z	RawAccZ_mean	RawAccZ_median	RawAccZ_max	RawAccZ_min	RawAccZ_rms
		Mag	RawAccMag_mean	RawAccMag_median	RawAccMag_max	RawAccMag_min	RawAccMag_rms
	Earth[a]	X	SfAccX_mean	SfAccX_median	SfAccX_max		
		Y	SfAccY_mean	SfAccY_median	SfAccY_max	SfAccY_min	SfAccY_rms
		Z	SfAccZ_mean	SfAccZ_median	SfAccZ_max	SfAccZ_min	SfAccZ_rms
		Mag	SfAccMag_mean	SfAccMag_median	SfAccMag_max	SfAccMag_min	SfAccMag_rms
Gyroscope	Raw	X	RawGyroX_mean	RawGyroX_median	RawGyroX_max		
		Y	RawGyroY_mean	RawGyroY_median	RawGyroY_max	RawGyroX_min	RawGyroX_rms
		Z	RawGyroZ_mean	RawGyroZ_median	RawGyroZ_max	RawGyroZ_min	RawGyroZ_rms
		Mag	RawGyroMag_mean	RawGyroMag_median	RawGyroMag_max	RawGyroMag_min	RawGyroMag_rms
	Earth	X	SfGyroX_mean	SfGyroX_median	SfGyroX_max	SfGyroX_min	SfGyroX_rms
		Y	SfGyroY_mean	SfGyroY_median	SfGyroY_max	SfGyroY_min	SfGyroY_rms
		Z	SfGyroZ_mean	SfGyroZ_median	SfGyroZ_max	SfGyroZ_min	SfGyroZ_rms
		Mag	SfGyroMag_mean	SfGyroMag_median	SfGyroMag_max	SfGyroMag_min	SfGyroMag_rms
Magnetometer	Raw	X	RawMagX_mean	RawMagX_median	RawMagX_max	RawMagX_min	RawMagX_rms
		Y	RawMagY_mean	RawMagY_median	RawMagY_max	RawMagY_min	RawMagY_rms
		Z	RawMagZ_mean	RawMagZ_median	RawMagZ_max	RawMagZ_min	RawMagZ_rms
		Mag	RawMagMag_mean	RawMagMag_median	RawMagMag_max	RawMagMag_min	RawMagMag_rms
	Earth	X	SfMagX_mean	SfMagX_median	SfMagX_max	SfMagX_min	SfMagX_rms
		Y	SfMagY_mean	SfMagY_median	SfMagY_max	SfMagY_min	SfMagY_rms
		Z	SfMagZ_mean	SfMagZ_median	SfMagZ_max	SfMagZ_min	SfMagZ_rms
		Mag	SfMagMag_mean	SfMagMag_median	SfMagMag_max	SfMagMag_min	SfMagMag_rms
	Roll		Roll_mean	Roll_median	Roll_max	Roll_min	Roll_rms
	Pitch		Pitch_mean	Pitch_median	Pitch_max	Pitch_min	Pitch_rms
	Yaw		Yaw_mean	Yaw_median	Yaw_max	Yaw_min	Yaw_rms

[a] relative to the ERF

Table B.2: Extracted features for the eating movement classification - Part 2

			Standard Deviation	**Median Deviation**	**Interquartile Range**	**Minimum Average**
Accelerometer	Raw	X	RawAccX_std	RawAccX_medianDev	RawAccX_iqr	RawAccX_minAvg
		Y	RawAccY_std	RawAccY_medianDev	RawAccY_iqr	RawAccY_minAvg
		Z	RawAccZ_std	RawAccZ_medianDev	RawAccZ_iqr	RawAccZ_minAvg
		Mag	RawAccMag_std	RawAccMag_medianDev	RawAccMag_iqr	RawAccMag_minAvg
	Earth[a]	X	SfAccX_std	SfAccX_medianDev	SfAccX_iqr	SfAccX_minAvg
		Y	SfAccY_std	SfAccY_medianDev	SfAccY_iqr	SfAccY_minAvg
		Z	SfAccZ_std	SfAccZ_medianDev	SfAccZ_iqr	SfAccZ_minAvg
		Mag	SfAccMag_std	SfAccMag_medianDev	SfAccMag_iqr	SfAccMag_minAvg
Gyroscope	Raw	X	RawGyroX_std	RawGyroX_medianDev	RawGyroX_iqr	RawGyroX_minAvg
		Y	RawGyroY_std	RawGyroY_medianDev	RawGyroY_iqr	RawGyroY_minAvg
		Z	RawGyroZ_std	RawGyroZ_medianDev	RawGyroZ_iqr	RawGyroZ_minAvg
		Mag	RawGyroMag_std	RawGyroMag_medianDev	RawGyroMag_iqr	RawGyroMag_minAvg
	Earth	X	SfGyroX_std	SfGyroX_medianDev	SfGyroX_iqr	SfGyroX_minAvg
		Y	SfGyroY_std	SfGyroY_medianDev	SfGyroY_iqr	SfGyroY_minAvg
		Z	SfGyroZ_std	SfGyroZ_medianDev	SfGyroZ_iqr	SfGyroZ_minAvg
		Mag	SfGyroMag_std	SfGyroMag_medianDev	SfGyroMag_iqr	SfGyroMag_minAvg
Magnetometer	Raw	X	RawMagX_std	RawMagX_medianDev	RawMagX_iqr	RawMagX_minAvg
		Y	RawMagY_std	RawMagY_medianDev	RawMagY_iqr	RawMagY_minAvg
		Z	RawMagZ_std	RawMagZ_medianDev	RawMagZ_iqr	RawMagZ_minAvg
		Mag	RawMagMag_std	RawMagMag_medianDev	RawMagMag_iqr	RawMagMag_minAvg
	Earth	X	SfMagX_std	SfMagX_medianDev	SfMagX_iqr	SfMagX_minAvg
		Y	SfMagY_std	SfMagY_medianDev	SfMagY_iqr	SfMagY_minAvg
		Z	SfMagZ_std	SfMagZ_medianDev	SfMagZ_iqr	SfMagZ_minAvg
		Mag	SfMagMag_std	SfMagMag_medianDev	SfMagMag_iqr	SfMagMag_minAvg
	Roll		Roll_std	Roll_medianDev	Roll_iqr	Roll_minAvg
	Pitch		Pitch_std	Pitch_medianDev	Pitch_iqr	Pitch_minAvg
	Yaw		Yaw_std	Yaw_medianDev	Yaw_iqr	Yaw_minAvg

[a] relative to the ERF

Table B.3: Extracted features for the eating movement classification - Part 3

			Maximum Average	**Peak Height**	**Average Peak Height**	**Mean Cross Count**
Accelerometer	Raw	X	RawAccX_maxAvg	RawAccX_peakHeight	RawAccX_peakHeightAvg	RawAccX_meanCrossCount
		Y	RawAccY_maxAvg	RawAccY_peakHeight	RawAccY_peakHeightAvg	RawAccY_meanCrossCount
		Z	RawAccZ_maxAvg	RawAccZ_peakHeight	RawAccZ_peakHeightAvg	RawAccZ_meanCrossCount
		Mag	RawAccMag_maxAvg	RawAccMag_peakHeight	RawAccMag_peakHeightAvg	RawAccMag_meanCrossCount
	Earth[a]	X	SfAccX_maxAvg	SfAccX_peakHeight	SfAccX_peakHeightAvg	SfAccX_meanCrossCount
		Y	SfAccY_maxAvg	SfAccY_peakHeight	SfAccY_peakHeightAvg	SfAccY_meanCrossCount
		Z	SfAccZ_maxAvg	SfAccZ_peakHeight	SfAccZ_peakHeightAvg	SfAccZ_meanCrossCount
		Mag	SfAccMag_maxAvg	SfAccMag_peakHeight	SfAccMag_peakHeightAvg	SfAccMag_meanCrossCount
Gyroscope	Raw	X	RawGyroX_maxAvg	RawGyroX_peakHeight	RawGyroX_peakHeightAvg	RawGyroX_meanCrossCount
		Y	RawGyroY_maxAvg	RawGyroY_peakHeight	RawGyroY_peakHeightAvg	RawGyroY_meanCrossCount
		Z	RawGyroZ_maxAvg	RawGyroZ_peakHeight	RawGyroZ_peakHeightAvg	RawGyroZ_meanCrossCount
		Mag	RawGyroMag_maxAvg	RawGyroMag_peakHeight	RawGyroMag_peakHeightAvg	RawGyroMag_meanCrossCount
	Earth	X	SfGyroX_maxAvg	SfGyroX_peakHeight	SfGyroX_peakHeightAvg	SfGyroX_meanCrossCount
		Y	SfGyroY_maxAvg	SfGyroY_peakHeight	SfGyroY_peakHeightAvg	SfGyroY_meanCrossCount
		Z	SfGyroZ_maxAvg	SfGyroZ_peakHeight	SfGyroZ_peakHeightAvg	SfGyroZ_meanCrossCount
		Mag	SfGyroMag_maxAvg	SfGyroMag_peakHeight	SfGyroMag_peakHeightAvg	SfGyroMag_meanCrossCount
Magnetometer	Raw	X	RawMagX_maxAvg	RawMagX_peakHeight	RawMagX_peakHeightAvg	RawMagX_meanCrossCount
		Y	RawMagY_maxAvg	RawMagY_peakHeight	RawMagY_peakHeightAvg	RawMagY_meanCrossCount
		Z	RawMagZ_maxAvg	RawMagZ_peakHeight	RawMagZ_peakHeightAvg	RawMagZ_meanCrossCount
		Mag	RawMagMag_maxAvg	RawMagMag_peakHeight	RawMagMag_peakHeightAvg	RawMagMag_meanCrossCount
	Earth	X	SfMagX_maxAvg	SfMagX_peakHeight	SfMagX_peakHeightAvg	SfMagX_meanCrossCount
		Y	SfMagY_maxAvg	SfMagY_peakHeight	SfMagY_peakHeightAvg	SfMagY_meanCrossCount
		Z	SfMagZ_maxAvg	SfMagcZ_peakHeight	SfMagZ_peakHeightAvg	SfMagZ_meanCrossCount
		Mag	SfMagMag_maxAvg	SfMagMag_peakHeight	SfMagMag_peakHeightAvg	SfMagMag_meanCrossCount
	Roll		Roll_maxAvg	Roll_peakHeight	Roll_peakHeightAvg	Roll_meanCrossCount
	Pitch		Pitch_maxAvg	Pitch_peakHeight	Pitch_peakHeightAvg	Pitch_meanCrossCount
	Yaw		Yaw_maxAvg	Yaw_peakHeight	Yaw_peakHeightAvg	Yaw_meanCrossCount

[a] relative to the ERF

Table B.4: Extracted features for the eating movement classification - Part 4

			Energy	**Entropy**	**Skewness**	**Kurtosis**
Accelerometer	Raw	X	RawAccX_energy	RawAccX_entropy	RawAccX_skewness	RawAccX_kurtosis
		Y	RawAccY_energy	RawAccY_entropy	RawAccY_skewness	RawAccY_kurtosis
		Z	RawAccZ_energy	RawAccZ_entropy	RawAccZ_skewness	RawAccZ_kurtosis
		Mag	RawAccMag_energy	RawAccMag_entropy	RawAccMag_skewness	RawAccMag_kurtosis
	Earth[a]	X	SfAccX_energy	SfAccX_entropy	SfAccX_skewness	SfAccX_kurtosis
		Y	SfAccY_energy	SfAccY_entropy	SfAccY_skewness	SfAccY_kurtosis
		Z	SfAccZ_energy	SfAccZ_entropy	SfAccZ_skewness	SfAccZ_kurtosis
		Mag	SfAccMag_energy	SfAccMag_entropy	SfAccMag_skewness	SfAccMag_kurtosis
Gyroscope	Raw	X	RawGyroX_energy	RawGyroX_entropy	RawGyroX_skewness	RawGyroX_kurtosis
		Y	RawGyroY_energy	RawGyroY_entropy	RawGyroY_skewness	RawGyroY_kurtosis
		Z	RawGyroZ_energy	RawGyroZ_entropy	RawGyroZ_skewness	RawGyroZ_kurtosis
		Mag	RawGyroMag_energy	RawGyroMag_entropy	RawGyroMag_skewness	RawGyroMag_kurtosis
	Earth	X	SfGyroX_energy	SfGyroX_entropy	SfGyroX_skewness	SfGyroX_kurtosis
		Y	SfGyroY_energy	SfGyroY_entropy	SfGyroY_skewness	SfGyroY_kurtosis
		Z	SfGyroZ_energy	SfGyroZ_entropy	SfGyroZ_skewness	SfGyroZ_kurtosis
		Mag	SfGyroMag_energy	SfGyroMag_entropy	SfGyroMag_skewness	SfGyroMag_kurtosis
Magnetometer	Raw	X	RawMagX_energy	RawMagX_entropy	RawMagX_skewness	RawMagX_kurtosis
		Y	RawMagY_energy	RawMagY_entropy	RawMagY_skewness	RawMagY_kurtosis
		Z	RawMagZ_energy	RawMagZ_entropy	RawMagZ_skewness	RawMagZ_kurtosis
		Mag	RawMagMag_energy	RawMagMag_entropy	RawMagMag_skewness	RawMagMag_kurtosis
	Earth	X	SfMagX_energy	SfMagX_entropy	SfMagX_skewness	SfMagX_kurtosis
		Y	SfMagY_energy	SfMagY_entropy	SfMagY_skewness	SfMagY_kurtosis
		Z	SfMagZ_energy	SfMagZ_entropy	SfMagZ_skewness	SfMagZ_kurtosis
		Mag	SfMagMag_energy	SfMagMag_entropy	SfMagMag_skewness	SfMagMag_kurtosis
	Roll		Roll_energy	Roll_entropy	Roll_skewness	Roll_kurtosis
	Pitch		Pitch_energy	Pitch_entropy	Pitch_skewness	Pitch_kurtosis
	Yaw		Yaw_energy	Yaw_entropy	Yaw_skewness	Yaw_kurtosis

[a] relative to the ERF

Appendix C

Detailed evaluation information of the classification algorithms

C.1 Confusion Matrices

	true FEED	true NOT_FEED
pred. FEED	93	5
pred. NOT_FEED	37	464

Figure C.1: Confusion matrix for the Decision Tree classifier

	true FEED	true NOT_FEED
pred. FEED	105	5
pred. NOT_FEED	25	464

Figure C.2: Confusion matrix for the k-NN classifier

	true FEED	true NOT_FEED
pred. FEED	92	14
pred. NOT_FEED	38	455

Figure C.3: Confusion matrix for the Naive Bayes classifier

	true FEED	true NOT_FEED
pred. FEED	88	19
pred. NOT_FEED	42	450

Figure C.4: Confusion matrix for the SVM classifier

C.2 ROC-Curves

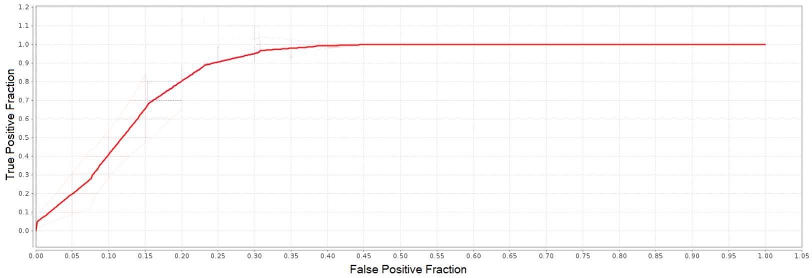

Figure C.5: ROC-curve for the Decision Tree classifier

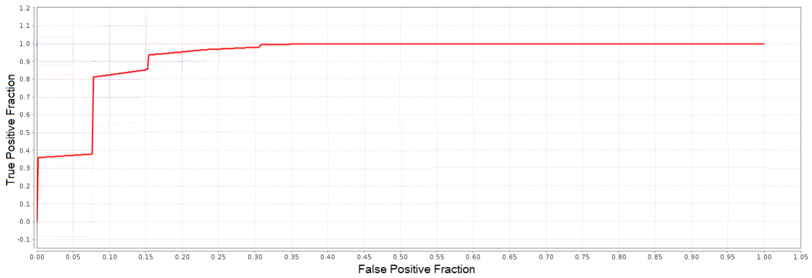

Figure C.6: ROC-curve for the k-NN classifier

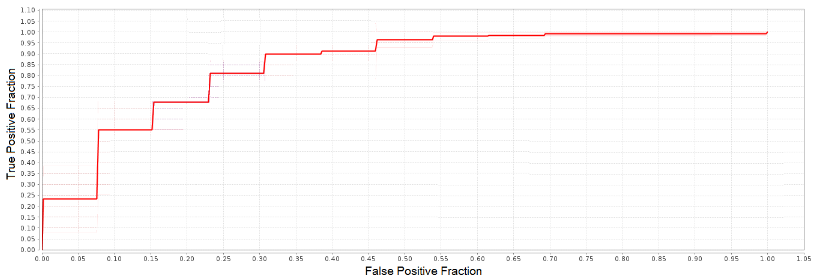

Figure C.7: ROC-curve for the Naive Bays classifier

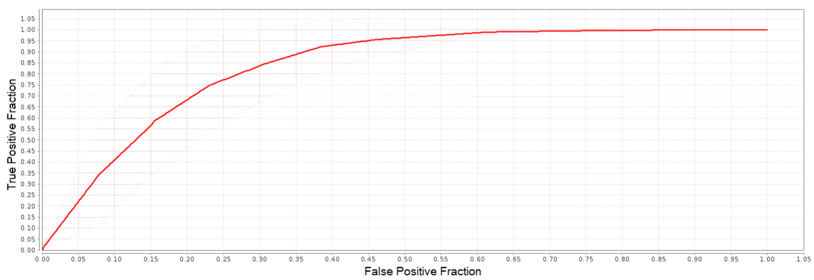

Figure C.8: ROC-curve for the SVM classifier